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Assessing the impact of managerial actions on OEE elements in global automotive production operations

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Abstract
As a well-known sector in terms of advancements, the automotive industry constantly faces challenges regarding lower production outputs due to significant efficiency losses and high costs. Managers face many implications in the current production scenario, where Industry 4.0 is developing rapidly and a lot of real-time data is available. While existing research developed models to predict the holistic performance of production operations, it remains unclear how managerial actions contribute to detailed Overall Equipment Effectiveness (OEE) elements. This study addresses the gap of predicting the impact of managerial actions on detailed elements of production operations in the automotive industry. Relying on 119 annual reports from 2023 of global automotive firms, this research applies text mining and regression analysis to develop a predictive framework. The results show a nuanced positive impact of managerial actions theorized within Total Productive Maintenance (TPM), Lean Management (LM), and Total Quality Management (TQM) on respectively the availability, performance, and quality element of the OEE. Theoretically, this is the first study to develop a predictive framework to assess the impact of managerial actions on detailed OEE elements of production operations in the global automotive industry. Practically, the most effective management practices to improve detailed OEE elements in this setting are identified.

Keywords: Automotive industry, Managerial actions, Overall Equipment Effectiveness (OEE), Text mining, Regression analysis

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1. Introduction

The automotive industry is a well-known sector in terms of advancements. Innovations enhancing vehicle safety, optimizing performance, and managing of automated systems have already started evolving in the past (Jiménez, 2017; Traub et al., 2017). Due to the increasing amount of sensors, actuators, communication systems and software components within vehicles, there is an increased connectivity between vehicles and their environment. Regarding electric vehicles, data is constantly exchanged with the smart grid. Hence, the automotive industry stays at the forefront of engineering advancements (Arena & Pau, 2019; Parekh et al., 2022). The global market share of electric vehicles doubled in terms of sales to an amount of 6.6 million in 2021 (IEA, 2020). Moreover, electric vehicle cost and charging infrastructure are likely to be improved in the short term. This is a big step forward in societal development as this enables the reach for mainstream consumers (Liu et al., 2021; Ouyang et al., 2021). From an economic perspective, the global car sales grew to around 75.3 million automobiles in 2023, which is an increase compared to 2022 where this number accounted for 67.3 million automobiles. The number of sales are forecasted to keep rising through 2024 (Scotiabank, 2024). A very recent trend in the industry is the advent of Autonomous Vehicles driven by the integration of Artificial intelligence (AI). This trend poises for a bright future driving the adoption of technological advancements enhancing decision-making, operation, and safety and reliability (Garikapati & Shetiya, 2024). Thus, the automotive industry is a significant sector in terms of global technological, economic, and societal development.

However, manufacturing in the global automotive industry is constantly under pressure due to highly customizing customer expectations (Gyimesi & Berman, 2011). This can also be referred to as mass customization, which brings flexibility to the way customers can specify their individual needs. Therefore, automotive firms are challenged for more flexible but also robust production processes (Mourtzis & Doukas, 2014). Also, the International Automotive Task Force (IATF) comprises particular addenda for the automotive industry next to basic ISO 9001 requirements. The goal of the standard is to develop a quality management system for automotive production providing continual improvement and emphasizing defect prevention. Next to that, greater control and monitoring of suppliers to ensure a reduction of waste and variation in the supply chain (Gruszka & Misztal, 2017; Trofimova & Panov, 2019; Yadav et al., 2020). This puts manufacturing in the global automotive industry even more under pressure. Thus, the automotive industry is undergoing significant change to improve sustainable performance responding to more stringent regulations and changing locus of innovation (Ettlie et al., 2021). Hence, the main challenge the automotive industry is facing is a low production output due to significant efficiency losses and high costs. These factors also influence customer satisfaction (Mohmmed et al., 2024). The industry needs digitalization to gain a competitive advantage and increase in production quality (Haktanır et al., 2022). As the industry is changing rapidly, automotive manufacturers should adapt adequately to the mentioned dynamic conditions. Technological innovations are indeed pushing current practices forward with developments in digitalisations, big data, and prediction (Savolainen et al., 2020).

Industry 4.0 is one of these developments bringing systems together to capture and record large amounts of data enhancing better decision-making in future smart factories (Shah et al., 2018). Unlike traditional optimization techniques, AI has the ability to independently interpret and learn from external data to achieve specific outcomes via flexible adaption. To identify underlying rules and patterns in data that are otherwise challenging to recognize, AI relies on machine learning (ML) approaches (Kaplan & Haenlein, 2019). In other words, ML is an application of AI that provides systems the ability to learn and improve from experience without being explicitly programmed automatically to do so. This allows systems to optimize processing accuracy and efficiency through recognizing patterns, extracting new information from data, and learning from experiences (Ayodele, 2010; Clifton et al., 2020). One example of such a technique that can be applied in manufacturing is predictive maintenance. Through effective utilization of condition monitoring and prediction information, it can significantly enhance equipment reliability and reduce maintenance costs, for instance in global automotive manufacturing processes (Kumar et al., 2018). Still, there are a number of implications facing managers regarding Industry 4.0 developments. Main managerial implications here involve investment and consulting costs, owning and supporting a digital strategy, and change management processes (Bousdekis et al., 2019). Therefore, it is of critical importance to assess managerial actions regarding optimalization of production operations in the current production scenario where there is a lot of historical data available in real time (Singh et al., 2023).

Ayadi et al. (2023) already showed that a prediction model had a significant impact on crucial KPIs like the OEE of production operations in an advanced automotive industry setting. However, the next challenge is to implement new models that can predict the effects of manager actions on production management, as compared to no action plans. There is a need to assess whether these actions will have a positive or negative effect. Mjimer et al. (2022) adds to that by stating that prediction contributes to the speed of having information and analysing it in an adequate way. This can avoid managers to take arbitrary decisions. Still, prediction of a KPI like the OEE could only give the holistic performance of production operations. While existing research has applied models to predict the holistic performance of production operations, it remains unclear how managerial actions contribute to detailed OEE elements. Thus, the research gap involves the need for a framework that can predict whether actions taken by managers have a positive or negative impact on detailed elements of production operations in the automotive industry. Based on the research gap and the scope, this study presents the following research question: *"How can a predictive framework be applied to assess the impact of managerial actions on OEE elements in global automotive production operations?"*

The aim of this research is to develop a framework that can predict whether actions taken by managers have a positive or negative impact on detailed OEE elements of production operations in the global automotive industry. This addresses the gap of predicting effects of managerial actions on production management. The novelty of this study lies in predicting OEE elements, which offers insight into how managerial actions impact these detailed aspects. This research provides a novel and innovative contribution to theory by developing a validated predictive framework based on text mining and regression analysis. This new method identifies the most significant predictors impacting detailed OEE elements and therefore provides a better understanding of how managerial actions affect operational performance. From a practical perspective, the ability to predict KPIs is crucial for process optimization and informed decision-making. Therefore, this research contributes to practice by offering a tool for assessing the whole automotive industry in predicting detailed OEE elements. Moreover, the findings show which managerial actions are the most effective and robust in improving OEE elements in global automotive production operations.

2. Theory

As there is a need to assess whether managerial actions have a positive or negative effect on OEE elements in the global automotive industry, literature regarding these topics needs to be reviewed (Ayadi et al., 2023; Mjimer et al., 2022). Table 1 gives an overview of the selected studies. The subsections below elaborate each topic extensively.

2.1 Predictive frameworks

Predictive frameworks are applied in multiple recent research. One example of such a technique is predictive maintenance, which optimizes the maintenance schedule in manufacturing. A study by Kumar et al. (2018) shows the contribution of machine learning techniques to condition-based maintenance prediction. In their research, they introduced a suitable big data analytics condition-based predictive maintenance model. The proposed framework outpaces classical methods in terms of classification accuracy and other statistical performance evaluation metrics.

In an automotive industry case study, Gamatié et al. (2019) applied supervised ML techniques to predict performance and energy consumption. The study focused on techniques among regression and classification. Within these techniques, the study applied Support Vector Machines, Adaptive Boosting, and Artificial Neural Networks. The results were validated showing very good outcomes with a limited set of training information.

Another study used a Classification And Regression Tree algorithm to develop a decision tree in a supervised way. This approach was applied to delivering components to the production area. For every component, the decision tree suggests a line feeding mode. The suggestion is based on selected attributes of the components and the manufacturing environment. Results show that the decision tree predicted with an average classification accuracy of 78.49% (Zangaro et al., 2021).

Rabby et al. (2024) integrated machine learning for inspecting and monitoring the curing state and mechanical performance of composite materials in an aerospace- and automotive setting. The study applied supervised machine learning algorithms (support vector machine and artificial neural network regression) to enhance manufacturing processes and quality control in the production of composite materials. This resulted in promising avenues in terms of accuracy and prediction.

In their study, Rajpathak et al. (2020) developed a classification system to automatically extract a domain ontology from repair data collected during the warranty period of an original equipment manufacturer (e.g. automotive). The system classifies key phrases into technical and non-technical classes. In addition, technical phrases are classified into part, symptom, or action classes. Results show an average F1 score of 0.82 and usage of the new ontology in fault detection and isolation in seven different fault models.

2.2 Overall Equipment Effectiveness (OEE)

A crucial performance metric in a manufacturing production efficiency setting is the Overall Equipment Effectiveness (OEE). Hence, it is a key performance indicator (KPI) used to measure equipment productivity. The OEE can be defined as “a productivity ratio between real manufacturing and what could be ideally manufactured” (Braglia et al., 2008; Ng Corrales et al., 2020; Olalere & Ramdass, 2024). The OEE consists of three aspects: availability, performance, and quality. Availability asks the question if the machine is running or not and measures downtime losses. Performance is about how fast the machine is running and measures speed losses. Quality concerns how many products satisfied the requirements and measures defect losses (Dunn, 2015; Jonsson & Lesshammar, 1999). Based on the reviewed literature, the OEE can be measured as follows:

OEE = availability x performance x quality

The next paragraphs will explain each of the three OEE elements in detail. Also, it provides an elaboration on how to calculate each element of the OEE. A detailed operationalization of the three elements into operational indicators will be given in the Methodology section.

A study about enhancing the OEE in Indonesian Automotive SMEs focused on a Total Productive Maintenance (TPM) approach. The study emphasized the need to address breakdowns in the machines, which was identified as the primary source of production losses. Data was collected about the current state of the machines. After that , post-implementation of improvements were initiated based on the TPM approach. The results show substantial enhancements in OEE. Reduction particularly in breakdowns validate the efficacy of TPM implementation, thus enhancing the availability aspect of the production. As availability measures downtime losses, it is a ratio that shows the utilisation of time available for machine or equipment operation activities expressed as a percentage (Sumasto et al., 2024). The availability element can be calculated as follows:

$$\text{Availability} = \frac{\text{Operating Time}}{\text{Loading Time}} \times 100\%$$

Figure 1, Calculation availability element

Recent research indicates that reduced production speeds are shown to consume 9-15% of available production capacity, which concerns the performance aspect. An analysis of production data revealed that technology and human factors have the strongest correlations with speed losses in the manufacturing industry. A framework of the factors related to speed loss is presented and investigated in a case study. This study resulted in a direct support in operational improvement initiatives due to the identified factors. Speed losses concern the performance aspect and can be conceptualized in interruptions or temporary malfunction, and speed loss from reduced run rates (Trattner et al., 2020). The performance element is thus a ratio indicating the ability of equipment or machinery to produce products expressed in percentages and can be calculated as follows (Sumasto et al., 2024):

$$\text{Performance} = \frac{\text{Output x Cycle Time}}{\text{Operating Time}} \times 100\%$$

Figure 2, Calculation performance element

A recent case study assessed the impact of quality improvement on production defectiveness in an automotive manufacturing industry. The study assesses the relationship between the implementation of quality control tools and the contribution of quality losses on OEE in the paint shop of automotive manufacturing plants. Important findings from the study are identified missing qualitative strategies and non-compliance with relevant ISO-8504 standards. The quality element is a ratio that considers quality standards and quality defects and can be calculated as follows (Olalere & Ramdass, 2024):

$$\text{Quality} = \frac{\text{Output - Defect Output}}{\text{Output}} \text{ x } 100\%$$

Figure 3, Calculation quality element

2.3 Managerial actions & Hypothesis development

The managerial theory of the firm is based on core management processes. These are direct consequences of the interactive development of managerial action, organizational context, and learning. Certain choices managers make within firms lead to managerial action. Then, organizational context is the consequence of the managerial action. Managerial processes in return are the outcome of an act of managerial choice. This shapes managerial formal roles and the interpretation of such roles by collective action (Ghoshal & Bartlett, 1994; Nardon, 2011).

In the context of this research, choices of managers leading to managerial actions can be conceptualized in theories related to availability, performance, and quality of the production operations. These corresponding theories are Total Productive Maintenance (TPM), Lean Management (LM), and Total Quality Management (TQM) (Bhadury, 2000; Hellsten & Klefsjö, 2000; Shah & Ward, 2007).

TPM reflects the availability element of the OEE, because it optimizes equipment effectiveness and promotes autonomous maintenance to eliminate breakdowns (Bhadury, 2000). There are several TPM initiatives and they involve an eight pillar implementation plan that should result in substantial increase in labour productivity. This is reached through controlled maintenance, reduction in maintenance costs, and reduced production stoppages and downtimes. The pillars consist of eight dimensions that represent the concept of TPM (Ahuja & Khamba, 2008). Figure 1 shows this conceptualization of managerial actions theorized within TPM, reflecting the availability element of the OEE. A detailed operationalization of the dimensions into operational indicators will be given in the Methodology section.

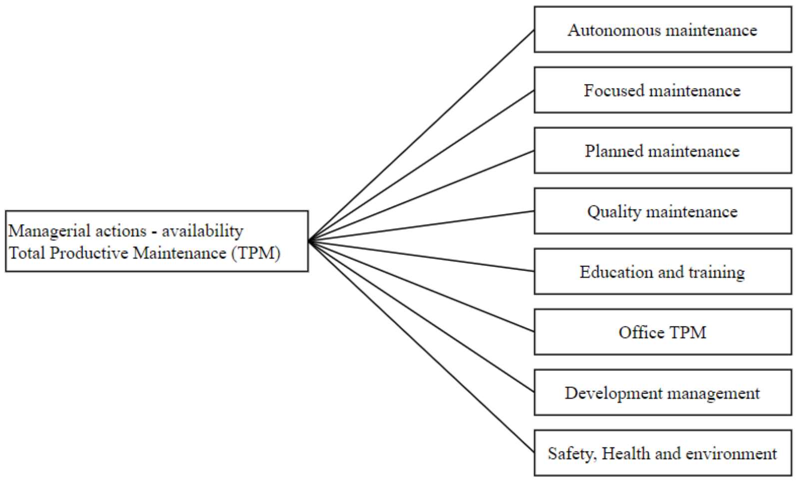

Figure 4, Managerial actions theorized within Total Productive Maintenance (TPM)

As TPM optimizes equipment effectiveness and promotes autonomous maintenance to eliminate breakdowns, this reflects the availability element of the OEE. Because the availability element measures downtime losses and expresses utilisation of time available for machine or equipment operation as a percentage, it is proposed that managerial actions with a higher degree of TPM positively impact the availability element of the OEE (Bhadury, 2000; Sumasto et al., 2024). Therefore, the following hypothesis is stated:
H1: Managerial actions with a higher degree of TPM positively impact the availability element of the OEE in global automotive production operations

LM is a socio-technical system whose main objective is to eliminate waste. In terms of production, this reflects the performance element of the OEE as one of the goals is to reduce internal variability which minimizes speed losses (Shah & Ward, 2007). LM of production is most frequently associated with elimination of waste commonly held by firms as excess capacity to ameliorate the effects of variability in processing time. Based on their research, Shah and Ward (2007) conceptualized internally related lean production in six dimensions that represent the concept of LM. Figure 2 shows this conceptualization of managerial actions theorized within LM, reflecting the performance element of the OEE. A detailed operationalization of the dimensions into operational indicators will be given in the Methodology section.

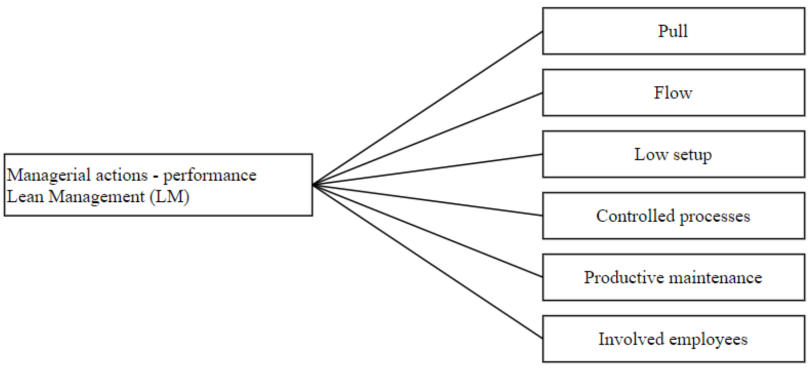

Figure 5, Managerial actions theorized within Lean Management (LM)

Speed losses consist of interruptions or temporary malfunction, and speed loss from reduced run rates. The performance element of the OEE measures these losses by expressing the ability of equipment or machinery to produce products in percentages. As the LM theory aims to reduce internal variability to minimize those speed losses, it is proposed that managerial actions with a higher degree of LM positively impact the performance element of the OEE (Shah & Ward, 2007; Sumasto et al., 2024; Trattner et al., 2020). Therefore, the following hypothesis is stated:
H2: Managerial actions with a higher degree of LM positively impact the performance element of the OEE in global automotive production operations

TQM is an approach to enhance the quality element of the OEE as the aim of this continuously evolving management system is to increase customer satisfaction with a reduced amount of resources. Thus, its goal is to produce against quality standards and reduce quality defects (Hellsten & Klefsjö, 2000). The concept of TQM is often described as a management philosophy. This philosophy is based on a number of core values, in literature also called dimensions. According to Hellsten (1997), a number of core values/dimensions seem to be common in most descriptions of TQM. Figure 3 shows the conceptualization of managerial actions theorized within TQM, reflecting the quality element of the OEE. A detailed operationalization into operational indicators will be given in the Methodology section.

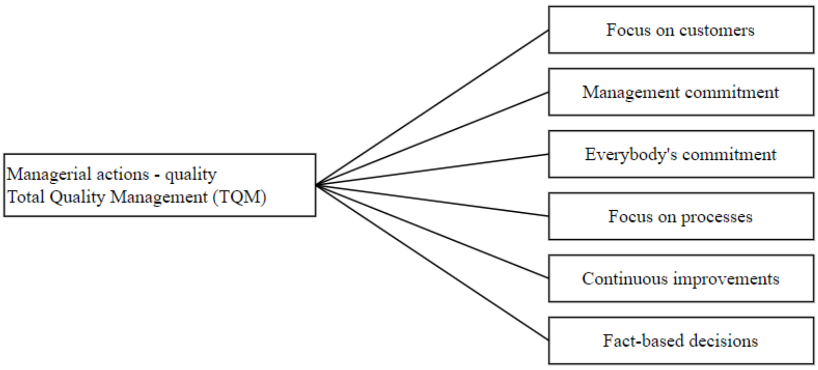

Figure 6, Managerial actions theorized within Total Quality Management (TQM)

TQM aims at increasing customer satisfaction with a reduced amount of resources. Therefore, the ultimate goal is to produce against quality standards and reduce quality defects. The quality element of the OEE takes into account these factor by expressing the total output minus defect output in a percentage of the total output. Because the goal of TQM is to reduce quality defects, it is proposed that managerial actions with a higher degree of TQM positively impact the quality element of the OEE (Hellsten & Klefsjö, 2000; Olalere & Ramdass, 2024). Therefore, the following hypothesis is stated:
H3: Managerial actions with a higher degree of TQM positively impact the quality element of the OEE in global automotive production operations

Based on the research question, proposed theoretical constructs and conceptualization, the hypotheses are stated. The next section will dive deeper into where and how data is collected. Moreover, it will show how the theoretical dimensions are operationalized into observable indicators in order to extract and analyse the collected data to test the hypotheses.

Table 1. Studies examining Predictive frameworks, Overall Equipment Effectiveness, and Managerial actions in the global automotive industry

Authors, Theoretical foundation, and Research Aim	**Context and key variables**	**Findings**	**Limitations**	**Empirical setting**
Total productive maintenance: literature review and directions (Ahuja & Khamba, 2008).	Preventive maintenance, Productive maintenance, Reliability management, Critical success factors	Important issues in TPM, TPM implementation practices, and contribution of strategic TPM programmes.	The successful TPM implementation program is developed based on literature and should be tested in practice.	A systematic review of the published literature so far.
Overall Equipment Effectiveness of a manufacturing line and an integrated approach to assess system performance (Braglia et al., 2008).	Manufacturing systems, Process efficiency, Plant efficiency, Productive capacity	Successful highlights of the progressive degradation of the ideal cycle time. Explanation through bottleneck inefficiency, quality rate, and synchronisation-transportation problems.	OEEML fails to explain to which extent in process inventories support effectiveness.	Application on an automated line for engine basements production, developed losses classification structure.
Empirical model-based prediction focusing on performance and energy consumption, applied in an automotive case study (Gamatié et al., 2019).	Resource allocation, Application mapping, Model-based performance prediction, Machine learning	Confirmed effectiveness of AdaBoost and ANNs models by achieving promising prediction accuracy.	Learning scalability issue, mapping encoding needs more information about system characteristics.	Automotive application case study, generated off-line simulation data. Limited set of training information.
The dimension of quality of management through linking organizational context and managerial	Organizational context, Quality of management, Managerial action	A proposed model of dimensions of organizational context as a way to assess an organization's	Theorizing from a single and, by definition, unique case is inevitably suspect.	A longitudinal field-study in one company.

action (Ghoshal & Bartlett, 1994).		quality of management.		
Values, techniques and tools of TQM as a management system (Hellsten & Klefsjö, 2000).	TQM, Techniques, Management styles	TQM should be viewed as a management system consisting of values, techniques and tools.	It needs to be assessed how the core values change over time and how the interpretation of them develops.	A brief discussion of literature of some of the problems with TQM and a discussion and description of the authors' own view.
The role of OEE in evaluation and improvement of manufacturing performance measurement systems (Jonsson & Lesshammar, 1999).	Effectiveness, Equipment, Manufacturing, Performance measurement	Identified dimensions and characteristics what should be and how to measure in a comprehensive overall manufacturing performance measurement system.	A broad present framework, should be further developed and tested.	Three case studies in medium- or large-sized manufacturing, interviews and secondary data, field experiments and interviews.
A big data driven sustainable manufacturing framework for condition-based maintenance prediction (Kumar et al., 2018).	Data driven sustainable enterprise, Fuzzy unordered induction algo, Big data analytics, Condition-based maintenance, Machine learning techniques, Backward feature elimination	A method that outpaces the classical methods in terms of classification accuracy and other statistical performance evaluation metrics.	Presuming that the replaced maintenance equipment or failure component is restored is unreasonable. Therefore, considering faulty maintenances in times ahead of the research work is necessary.	Sophisticated simulator of a Gas Turbine, generated simulation data, 11934 instances for binary classification.
Culture, attention, and managerial action: an application of quantitative content analysis (Nardon, 2011).	Attention, Brazil, Culture, Cross-cultural management, National culture, Content analysis, Business periodicals	Culture influences action by directing collective attention to action alternatives.	Limitation of quantitative content analysis in capturing latent meaning.	Two best selling business periodicals from Brazil and US, content analysis.

A systematic literature review about an overview and different approaches of Overall Equipment Effectiveness (OEE) (Ng Corrales et al., 2020).	Overall equipment effectiveness, OEE, Systematic literature review, Model-based	OEE as an emerging topic that can be used as input information for decision-making in business and is related to maintenance, production, lean manufacturing, and optimization.	This systematic literature review is a basis. Future relevant studies should follow up on this.	862 articles obtained in a general search, 186 articles used for the review obtained from Web of Science and Scopus.
The impact of quality improvement on production defectiveness in an automotive manufacturing industry (Olalere & Ramdass, 2024).	Overall equipment efficiency, Nonconformities, Quality defects, Automotive paint-shop, Quality tools, First time capability	Identified missing qualitative strategies and non-compliance with relevant ISO-8504 standards.	The subjective experience of each worker in generalizing the data across other industries.	Assessment in the paint shop of automotive manufacturing plants, evaluating production defects and identifying non-conformities.
A rapid non-destructive quality inspection technique for composites using machine learning techniques (Rabby et al., 2024).	Degree of cure, Dielectric properties, Machine learning, Tensile strength	An accurate classification of the curing state with 96.7% accuracy and an accuracy of 87.5% regarding prediction of tensile strength.	Limitations associated with specific fiber orientations, increasing number of classes, and creating large datasets.	Different cured samples using broadband dielectric spectroscopy, three datasets consisting of dielectric measurements (80-100 samples).
An integrated framework for automatic ontology learning using a hierarchical classification system (Rajpathak et al., 2020).	Ontology learning, Automotive, Supervised machine learning, Decision support	Achievement of the average F1 score of 0.82 and usage of the new ontology in fault detection and isolation in seven different fault models.	New ontology in timely fault detection and isolation for improved root cause investigation should be utilized.	Randomly selected warranty repair data sold by General Motors, subset containing 1.3 million verbatims.
Lean production and defining and developing	Lean production, Scale development, Confirmatory factor analysis	A mapped operational space corresponding to conceptual	Specific research design that was used and specific	Various components from past literature, data from a large set

measures (Shah & Ward, 2007).		space surrounding lean production.	results of the study.	of manufacturing firms.
Enhancing manufacturing operations through optimizing OEE using a TPM approach (Sumasto et al., 2024).	Automotive parts, Manufacturing, OEE, TPM, Six big losses, SMEs	Valuable insights into enhancing operational efficiency through a comprehensive analysis of OEE and identifying key areas for improvement.	Findings are based on a single case study within the Indonesian automotive sector.	Extensive literature review on TPM and OEE, Indonesian automotive SME sector involving initial survey and post-implementation of improvements.
A framework of factors related to speed loss in process manufacturing (Trattner et al., 2020).	Speed loss, Total productive maintenance, Overall equipment effectiveness, Productivity, Process industry	A developed framework including 20 factors contributing to speed loss in manufacturing lines, with nine significant factors and multiple interaction effects.	Determination of speed targets might have been skewed by outliers and possible measurement errors in the sensors.	Literature review, case study of two production lines to investigate this framework, analysis of the production data
Classification And Regression Tree for the optimalisation of the assembly line feeding mode selection (Zangaro et al., 2021).	Classification tree, Line feeding problem, Machine learning, Optimalisation, Part feeding	An enhanced optimisation model for the Line feeding problem.	The repair approach that had to be developed. This is a limitation due to the high number of constraints.	Data synthetically generated from data sets of four manufacturing companies, 540.000 rows in each sample.

3. Methodology

3.1 Research context

As already stated in the Introduction, the automotive industry is a well-known sector in terms of global development and advancements. Recent trends indicate that the automotive industry is at the forefront of technological advancements. However, we also saw that the industry is constantly under pressure due to highly customizing customer expectations, the IATF, and a global shift towards sustainable practices. Technological innovations can offer a solution, for example predicting elements of production operations by using AI/ML optimization techniques. Still, predicting whether managerial actions have a positive or negative effect on OEE elements is unclear. A review of recent literature showed the application of predictive frameworks in multiple automotive industry settings. It also showed that managerial actions with a higher degree of TPM, LM, and TQM are likely to positively impact the detailed elements of the OEE (Ayadi et al., 2023; Gruszka & Misztal, 2017; Gyimesi & Berman, 2011; Jiménez, 2017; Kaplan & Haenlein, 2019; Mjimer et al., 2022; Traub et al., 2017; Trofimova & Panov, 2019; Yadav et al., 2020).

Therefore, this study investigates how a predictive framework can be applied to assess the impact of managerial actions on OEE elements in global automotive production operations. Addressing this problem in the global automotive industry is highly relevant as this contributes to SDG 12: "sustainable consumption and production". This because one of the identified dominant vantage points regarding this SDG is a focus on more efficient production methods and products. An enhancement in the OEE (i.e. because of a positive impact of managerial action) leads to a better productivity ratio between real manufacturing and what could ideally be manufactured, thus improving efficiency (Bengtsson et al., 2018; Braglia et al., 2008; Ng Corrales et al., 2020; Olalere & Ramdass, 2024).

3.2 Research design

According to the research question, this research takes a quantitative approach, aiming to assess how a framework can be applied to assess the impact of managerial actions on OEE elements in global automotive production operations. Therefore, a systematic annual report review from big automotive firms is used as a data collection method. Thus, automotive firms are selected based on a set of objective criteria and their respective annual reports are downloaded and stored in a structured and reproducible way. A systematic approach is choses, because this ensures explicit, systematic methods that aim to minimize bias in order to produce more reliable findings to inform decision making. Instead of identifying, appraising and synthesizing all the empirical evidence regarding the research question, annual reports from big automotive firms are reviewed (Kunisch et al., 2023). This origin of data is chosen as previous studies show that annual reports provide relevant information for research in the automotive industry as it obtained homogeneous subjects offering real and verifiable data (MacGregor Pelikánová, 2019). Also, organizational documents, for instance annual reports, are particularly rich and valuable data. They can provide insight into managerial cognition for example (Pollach, 2012).

Quantitative content analysis is used to extract and structure data from the annual reports. Relying on a coding scheme of predefined indicators operationalized from the theoretical constructs, the presence and frequency of indicators per dimension at individual company level are identified. This leads to a structured dataset, where the independent variables reflect the dimensions of TPM, LM, and TQM. The dependent variables here concern the availability, performance, and quality element of the OEE. As assessing the impact of managerial actions on OEE elements is important but a difficult-to-study issue, content analysis is promising for rigorous exploration (Carley, 1993; Morris, 1994; Woodrum, 1984). Also, other research already examined the content of corporate disclosures and its impact on economic performance based on analyses of annual reports. This is suitable as an enhancement in the OEE improves efficiency, thus impacting economic performance (Bühner & Müller, 1985; Ingram & Frazier, 1983; McConnell et al., 1986).

As this study uses existing knowledge and theory to empirically test the impact of managerial actions on OEE elements, text mining is applied as a tool to assist the process of data extraction through quantitative content analysis from the annual reports. Instead of manually identifying the presence and frequency of indicators at individual company level, statistical software is used to automate this task to ensure a consistent and replicable procedure. This is suitable in this context, because text mining helps accelerating knowledge discovery by radically increasing the amount of data that can be analysed (Kobayashi, Mol, Berkers, Kismihók, et al., 2018). Moreover, text mining reduces bias of potentially unreliable manual procedures and makes classification convenient, fast, and reliable creating potential for application in organizational research (Kobayashi, Mol, Berkers, Kismihok, et al., 2018). After collecting, extracting, and analysing the data, the hypotheses are tested. How the data is exactly extracted and structured and how the hypotheses are tested will be explained in detail in the next paragraphs.

3.3 Research object

The data used in order to answer the research question are collected via ORBIS, one of the world's largest data resources covering around 55 million companies from all over the world. The ORBIS database organizes firm's public data from administrative sources and filters them into various standard formats. This facilitates searching and objective criteria in terms of selecting automotive firms and the time frame of the collected annual reports (BUREAU, 2009; Ribeiro et al., 2010). For this research, annual report data is used from global automotive manufacturers. The choice of these firms relies on their highest annual revenue in order to select the annual reports in a structured way (Hoeft, 2021; Jankovic-Zugic et al., 2023). Based on their highest annual revenue, the firms are ranked. From those firms, the available annual report from 2023 is selected.

3.4 Data collection

After the relevant firms are identified in a structured way, the available annual reports from 2023 from these firms are collected. In order to extract and structure the data, the methodological measurement of content analysis is applied to the text in the annual reports for the purpose to extract and structure the valuable data needed to test the hypotheses (Shapiro & Markoff, 2020). Content analysis provides an advantage here as it includes a quantitative component, this is needed in order to statistically test the hypotheses (Duriau et al., 2007). As this research aims to test existing theory regarding managerial actions impacting OEE in the global automotive industry, the coding approach is deductive. Based on the reviewed literature and the stated hypotheses, the variables are explicit from the outset and therefore deductive coding is required (Eriksson & Kovalainen, 2015; Rosenbusch et al., 2013). As this research collects "big" text data, text mining is used to enable efficient and reliable text analysis. This tool discovers and extracts interesting, non-trivial knowledge from free or unstructured text and derives knowledge from patterns and relationships. This can be used to reveal facts, trends, or constructs which is valuable input for testing the hypotheses (Gupta & Lehal, 2009; Harlow & Oswald, 2016; Kao & Poteet, 2007). RStudio is used as software to conduct the text mining process.

3.5 Operationalization and validation

In Figure 7, the applied coding scheme is provided. The scheme describes the following elements: independent and dependent variables, data, quality, and quantitative information. This uniformed and standardised process enhances direction in data reduction and organization (Gaur & Kumar, 2018). The coding scheme forms a foundation for the process of content analysis applying text mining. The independent and dependent variables are conceptualized into dimensions in the Theory section. The coding scheme follows up this foundation by operationalizing the dimensions into operational indicators. For example, Productive maintenance is one of the dimensions representing managerial actions theorized within LM. In return, "address equipment downtime", "equipment availability", and "preventive maintenance" are the operational indicators reflecting the dimension Productive maintenance. The transformation from theoretical constructs to dimensions, and from dimensions to operational indicators are based on the collected theories in reviewing the relevant literature. Operationalizing the theoretical constructs in this structured manner is of critical importance, because authors often mention issues around the operationalization of variables, proper item and scale development, and measurement and operationalization of constructs (Aguinis et al., 2009). To ensure that the operational indicators reflect the theoretical dimensions, a systematic literature review per dimension is conducted. For each dimension, ten definitions of ten different articles are collected to extract operational indicators. Based on this systematic review, the coding scheme is expanded to establish content validity (see Appendix 1) (Kerlinger, 1966). In addition, the expanded and validated coding scheme is compared to English dictionaries to strengthen the eventual establishment of construct validity (Hinkin & Tracey, 1999).

Independent variables:

Independent variable:	Dimensions:	Operational indicators:
Managerial actions- TPM	Autonomous maintenance	"operator ownership" "production equipment" "compliance"
	Focused maintenance	"16 losses" "FMEA analysis" "system efficiency" "OEE"
	Planned maintenance	"equipment life cycle" "PM check sheets" "MTBF, MTTR"
	Quality maintenance	"zero defects" "equipment problems" "root causes" "3M conditions"
	Education and training	"technological" "quality control" "interpersonal skills" "multi-skilling"
	Office TPM	"synergy" "cost-related issues" "5S"
	Development management	"new equipment" "transforming systems" "maintenance improvement"
	Safety, health and environment	"safe working environment" "incidents, injuries, accidents" "standard procedures"

Independent variable:	Dimensions:	Operational indicators:
Managerial actions- LM	Pull	"just in time production" "kanban" "pull production"
	Flow	"continuous flow" "workflow optimization" "SMED"
	Low setup	"downtime reduction" "changeover time" "setup time reduction"
	Controlled processes	"statistical process controll" "defect free units" "production consistency"
	Productive maintenance	"address equipment downtime" "equipment availability" "preventive maintenance"
	Involved employees	"employee involvement" "problem solving" "cross functional"

Independent variable:	Dimensions:	Operational indicators:
Managerial actions- TQM	Focus on customers	"customer surveys" "quality function deployment" "customer driven"
	Management commitment	"organizational culture" "leadership" "strategic quality"
	Everybody's commitment	"improvement groups" "quality circles" "specific tools"
	Focus on processes	"process management" "control charts" "process maps" "ISO certification"
	Continuous improvements	"continuous improvement" "Six Sigma" "learning" "defect reduction"
	Fact-based decisions	"data-driven decisions" "design of experiments" "statistical process control"

Dependent variable:

Dependent variable:	Dimensions:	Operational indicators:	Operational measurement:
OEE (Overall Equipment Effectiveness)	Availability	"breakdowns" "downtime" "operating time" "loading time"	$\frac{\text{Operating Time}}{\text{Loading Time}} \times 100\%$
	Performance	"speed loss" "interruption" "temporary malfunction" "output" "cycle time" "operating time"	$\frac{\text{Output x Cycle Time}}{\text{Operating Time}} \times 100\%$
	Quality	"quality loss" "quality standards" "quality defects" "output" "defect output"	$\frac{\text{Output - Defect Output}}{\text{Output}} \times 100\%$

Data:

Source	ORBIS: one of the world's largest data resources covering around 55 million companies worldwide.
Population	Global automotive manufacturing firms.
Selected firms (sample)	Top 125 global automotive manufacturing firms based on highest annual revenue and available annual report from 2023
Data	Annual reports from 2023

Quality:

ORBIS	Organized firm's public data from administrative sources and filtered into various standard formats, enhancing searching and objectivity.
Setting	Global automotive industry.

Quantity:

Sample size	Firms: n = 125, Annual reports: n = 125 (from 2023).

Figure 7, Coding scheme

3.6 Data analysis

The coding scheme forms a foundation for the text mining process. In the description of the independent and dependent variables, the constructs are defined, conceptualized, and operationalized into measurable indicators. The goal of the text mining model is to assign the category (for example TPM, LM, or TQM) and the dimension (for example autonomous maintenance) to a given text (Phan et al., 2008). Before applying the coding scheme to the data, a customized stop-word list is applied to the data to address threats to internal validity (see Appendix 2) (Turner et al., 2017). The stop-word list is customized based on the 50 most frequent terms identified in the data and a default stop-word list in RStudio. Classification is used as a technique to assign the extracted text elements to the predefined constructs and dimensions. These are the independent variables: managerial actions theorized within TPM, LM, and TQM including their dimensions and operationalized indicators, and the dependent variables: respective OEE elements - availability, performance, and quality including their operational indicators. Through the application of thematic categorization, the text data are assigned to those predefined constructs and dimensions (Kobayashi, Mol, Berkers, Kismihók, et al., 2018).

Before testing the hypotheses, a sample of the text mining results is analysed back to the original individual reports. Specifically, the keywords are analysed on how they appear in their exact textual context. This to ensure that which is measured really reflects what is believed to measure, thus enhancing construct validity (Lambert & Newman, 2023). In addition to this, the correlation between the obtained results and financial performance indicators is analysed. This correlation analysis is conducted to evaluate to which extent the annual report content represents an organizational context. Therefore, the obtained data is supplemented with Return on Capital Employed (ROCE), Asset Turnover Ratio, and Net Profit Margin of each individual company. These financial indicators are obtained from the ORBIS database. The correlation analysis is structured as follows: the TPM dimensions and the availability element of the OEE are correlated with ROCE, the LM dimensions and the performance element of the OEE are correlated with Asset Turnover Ratio, and the TQM dimensions and the quality element of the OEE are correlated with Net Profit Margin. After the obtained text data are thematically categorized to the dimensions and theoretical constructs through the operational indicators in the text mining process, the presence and the count of each dimension are stored in a dataset displaying these numbers on individual company level (Speer, 2021). This table forms the basis to test the hypotheses.

As the presence variables are categorial and the count variables are continuous, logistic regression and linear regression are two possible options to test the hypotheses. Initially, multiple linear regression is conducted to test the hypotheses and make inferences about the relative importance of predictor variables. Per hypothesis, the analysis tests whether the overall model fits, thus supporting or rejecting the hypothesis (i.e. TPM impacting availability). In addition, it indicates the relative importance of the predictor dimensions (i.e. autonomous maintenance) (Nimon et al., 2010; Zientek et al., 2008). To account for model deviations in different situations, robustness tests are applied to the initial regression analyses. This tackles the violations of the model assumptions about the data in empirical settings (Alfons et al., 2022). In testing the three hypotheses, the traditional level of α is used to assess the significance of the impact of managerial actions on OEE elements. This means the level of α is set at .05 (Cashen & Geiger, 2004).

4. **Results**

4.1 Obtained annual reports

To obtain annual reports from global automotive manufacturers in a structured and objective way, a search on ORBIS is conducted. The search steps involve Status: Active companies, NACE Rev. 2: 29 (Manufacture of motor vehicles, trailers and semi-trailers), and Operating revenue (Turnover): All companies with a known value (2023, 2024) for at least one of the selected periods. Table 2 provides the selected global automotive manufacturers with an available annual report of 2023.

Table 2. Selected global automotive manufacturers

Number	Firm	Operating revenue (Turnover) in USD	Last available year
1	Volkswagen AG	347.322.817	2024
2	Toyota Motor Corporation	298.150.909	2023
3	Stellantis NV	209.446.214	2023
4	General Motors Company	187.442.000	2024
5	Ford Motor Company	184.992.000	2024
6	Mercedes-Benz Group AG	153.829.855	2024
7	Bayerische Motoren Werke AG	148.570.946	2024
8	Honda Motor CO., LTD	135.066.460	2023
10	Robert Bosch Gesellschaft mit Beschraenkter Haftung	106.893.328	2023
11	BYD Company Limited	106.368.059	2024
12	SAIC Motor Corporation Limited	104.137.259	2023
13	Tesla, Inc	97.690.000	2024
16	KIA Corporation	73.094.390	2024
17	Audi AG	67.070.315	2024
20	Renault	58.419.399	2024
21	Daimler Truck AG	56.903.645	2024
23	Tata Motors Limited	52.882.118	2023
24	Traton SE	49.697.837	2024
25	AB Volvo	47.862.989	2024
27	Denso Corporation	47.524.397	2023
30	Magna International Inc	42.836.000	2024
31	Beijing Automotive Group CO., LTD	40.082.941	2023

32	Hyundai Mobis CO., LTD	38.936.732	2024
33	Honeywell International Inc	38.498.000	2024
34	Volvo Car AB	36.561.437	2024
36	Suzuki Motor Corporation	35.532.264	2023
38	Paccar Inc	33.663.800	2024
40	Jaguar Land Rover Limited	32.446.927	2023
42	Mazda Motor Corporation	31.918.426	2023
43	Subara Corporation	31.117.990	2023
44	Weichai Power CO., LTD	29.713.539	2024
45	Forvia SE	28.893.458	2024
49	Great Wall Motor Company Limited	27.191.928	2024
51	Toyota Industries Corporation	25.493.355	2023
54	Lear Corporation	23.306.000	2024
55	Valeo	22.393.480	2024
56	Isuzu Motors Limited	22.391.246	2023
59	GAC Toyota Motor CO., LTD.	20.891.987	2023
60	PT Astra International TBK	20.589.035	2024
62	Scania CV Aktiebolag	20.328.036	2023
63	Li Auto Inc.	19.882.125	2024
65	Aptiv PLC	19.713.000	2024
68	Schaeffler AG	19.050.301	2024
70	Mitsubishi Motors Corporation	18.443.564	2023
71	Maruti Suzuki India Limited	17.014.702	2023
72	Chery Automobile CO., LTD.	16.967.775	2023
74	Ford Otomotive Sanayi A.S.	16.908.228	2024
75	Iveco Group NV	16.233.844	2024
76	Seat SAU	16.051.237	2023
77	Illinois Tool Works Inc.	15.898.000	2024
79	Dongfeng Motor Group Company Limited	15.290.717	2024

80	Mahindra & Mahindra Limited	14.835.830	2023
83	Borgwarner Inc.	14.086.000	2024
86	Sinotruck (Hong Kong) Limited	13.220.398	2024
87	GAC Honda Automobile CO., LTD	13.026.454	2023
89	Toyota Boshoku Corporation	12.965.283	2023
93	Gestamp Automocion CO., LTD	12.558.403	2024
95	Samvardhana Motherson International Limited	11.835.107	2023
97	Oshkosh Corporation	10.730.200	2024
101	Autoliv, Inc.	10.390.000	2024
102	Rheinmetall AG	10.299.650	2024
103	Dana Incorporated	10.284.000	2024
105	Jilin Henghao Technology CO., LTD	10.113.122	2023
106	Thor Industries, Inc.	10.043.408	2024
107	Hino Motors LTD	10.024.826	2023
112	Nissan Motor Manufacturing (UK) Limited	9.279.425	2023
113	Hyundai Motor Manufacturing Czech SRO	9.119.318	2023
115	Nio Inc.	9.061.690	2024
117	Kia Slovakia SRO	8.855.270	2023
120	Faw Jiefang Automotive CO., LTD	8.674.590	2023
125	Knorr-Bremse AG	8.263.407	2024
129	Hotai Motor CO., LTD	7.700.328	2024
130	Ningbo Joyson Electronic Corp.	7.652.313	2024
131	Linamar Corporation	7.376.941	2024
132	Toyoda Gosei CO LTD	7.103.550	2023
136	Ferrari NV	6.959.054	2024
143	Jiangling Motors Group CO., LTD	6.427.406	2024

146	Motus Holdings Limited	6.279.928	2024
148	American Axle & Manufacturing Holdings, Inc.	6.124.900	2024
151	HL Mando CO., LTD	6.019.171	2024
156	Xpeng Inc.	5.679.463	2024
160	Hyundai WIA Corporation	5.565.229	2024
162	Mahle Behr GMBH & CO. KG	5.314.570	2023
165	Terex Corporation	5.127.000	2024
167	Yutong Bus CO., LTD	5.106.382	2024
169	Nemak S.A.B. De CV	4.997.308	2023
170	Rivian Automotive, Inc.	4.970.000	2024
172	Ashok Leyland Limited	4.912.371	2023
174	Flex-N-Gate LLC	4.805.000	2024
177	Mitsubishi Logisnext CO LTD	4.639.802	2023
178	Grand Baoxin Auto Group Limited	4.637.728	2023
180	Inter Cars SA	4.601.667	2023
183	Trigano	4.378.590	2024
190	Hyster-Yale, Inc.	4.308.200	2024
192	Xian Geely Automobile CO., LTD	4.233.748	2023
194	TVS Holdings Limited	4.197.235	2023
195	Tokai Rika CO LTD	4.122.698	2023
197	Niterra CO. LTD	4.089.574	2023
198	Brembo SPA	4.037.245	2024
205	Visteon Corporation	3.866.000	2024
208	NGK Insulators, LTD	3.827.524	2023
211	LCI Industries	3.741.208	2024
212	Tofas Turk Otomobil Fabrikasi Anonim Sirketi	3.679.604	2024
221	DRB-Hicom Berhad	3.520.093	2023
222	CIMC Vehicles (Group) CO., LTD	3.510.708	2023
223	Martinrea International Inc.	3.489.302	2024

225	Garrett Motion Inc.	3.475.000	2024
226	Hiab OYJ	3.462.237	2024
228	Phinia Inc.	3.403.000	2024
229	SL Corporation	3.383.180	2024
235	Minth Group Limited	3.234.140	2024
237	Allison Transmission Holdings, Inc	3.225.000	2024
244	Trelleborg AB	3.126.139	2024
245	Stanley Electric CO., LTD	3.123.286	2023
246	NFI Group Inc	3.122.315	2024
247	Bentley Motors Limited	3.119.050	2023
254	Winnebago Industries, Inc	2.973.500	2024
267	Seoyonehwa CO., LTD	2.749.340	2024
268	Cooper-Standard Holdings Inc	2.730.893	2024
271	KG Mobility Corp.	2.656.510	2024
273	Yulon Motor CO., LTD	2.642.705	2024
284	Iochpe Maxion SA	2.476.964	2024
285	Zhuzhou Times New Material Technology CO., LTD	2.459.921	2023

The firms that are not included in Table 2 did not have an available annual report of 2023. The main reasons causing this are no available document of 2023 and the fact that the firm is part of another firm. Table 3 provides the firms with missing reports, including the reason.

Table 3. Missing Reports

Number	Automotive company	Reason
14	Nissan Motor CO, LTD	No document available
15	Stellantis Auto SAS	Part of Stellantis NV
18	Iran Khodro Industrial Group	No document available
19	Renault SAS	Part of Renault
22	Daimler Truck Holding AG	Part of Daimler Truck AG
26	Shiyan Cheyi Electronic Tech	No document available
28	BYD Auto Industry Company Limited	Part of BYD Company Limited
29	Wuhan Wuyue Plastic Industry	No document available
35	BMW Brilliance Automotive	Part of Bayerische Motoren Werke AG
37	Wuhan Xiaolaba Automobile	No document available
39	Tesla Shanghai CO, LTD	Part of Tesla, Inc.
41	Stellantis Europe SPA	Part of Stellantis NV
46	Volvo Personvagnar Aktiebolag	Part of Volvo Car AB
47+48	BAIC Motor Corporation Limited	Part of Beijing Automotive Group CO., LTD

50	Beijing Benz Automotive	Part of Beijing Automotive Group CO., LTD
52	HASCO	Only in Chinese language
53	BYD Automobile CO, LTD	Part of BYD Company Limited
58	Ford- Werke GMBH	Part of Ford Motor Company
61	SAIC Volkswagen	Part of SAIC Motor Corporation Limited
64	SAIC Motor Corporation Limited	Already encountered earlier
66	Seres Group CO, LTD	Only in Chinese language
67	SAIC General Motors CO., LTD	Part of SAIC Motor Corporation Limited
69	Stellantis Espana Sociedad Limitada	Part of Stellantis NV
73	Ford Motor Company Limited	Part of Ford Motor Company
78	Toyota Auto Body CO., LTD	Part of Toyota Motor Corporation
81	Guangzhou Automobile Group	Part of GAC Group
82	Wuhan Hezhongda Automotive Equipment CO., LTD	No document available
84	Volvo Lastvagnar Aktiebolag	Part of Volvo AB
85	Dongfeng Motor CO., LTD	Part of Dongfeng Motor Group Company Limited
88	Volkswagen Slovakia AS	Part of Volkswagen AG
90	Ford Motor Company SA DE VC	Part of Ford Motor Company
91	Dongfeng Honda Automobile CO., LTD	Part of Dongfeng Motor Group Company Limited
92	Bahman Group Company Public Joint Stock	No document available
94	Changsa BYD Automobile	Part of BYD Company Limited
96	Pon Holdings BV	No document available
98	GM Korea Company	Part of General Motors Company
99	Zeekr Intelligent Technology Holding LTD	No document available
100	Iran Khodro Diesl Public Joint Stock Company	No document available
102	Audi Hungaria Zartkoruen Mukodo Reszvenytarsasag	No document available
108	Iveco SPA	Part of Iveco Group NV
109	Toyota Motor Kyushu Inc	Part of Toyota Motor Corporation
110	SAIC-GM-Wulling Automobile CO., LTD	Part of SAIC Motor Corporation Limited
111	Dongfeng Motor CO., LTD Dongfeng Nissan Passenger Vehicle CO., LTD	Part of Dongfeng Motor Group
114	Hyundai Transys Inc	No document available
116	Nio Inc	Already encountered
118	Tesla Manufacturing Brandenburg SE	Part of Tesla, Inc
119	Volvo Car Belgium	Part of Volvo Car AB
121	Bosch Automotive Products (Suzhou) CO., LTD	Part of Robert Bosch Gesellschaft mit Beschraenkter Haftung
122	Hefei BYD Automobile CO., LTD	Part of BYD Company Limited
123	China First Automobile CO., LTD	Part of FAW Jiefang Automotive CO., LTD
126	FAW Jiefang Group CO., LTD	Part of FAW Jiefang Automotive CO., LTD
127	Renault Trucks	Part of Volvo Group
128	Daihatsu Motor CO., LTD	No document available
133	GAC Passenger Vehicle CO., LTD	Part of GAC Group
134	DAF Trucks NV	Part of Paccar Inc.
135	Weilai Automobile (Anhui) CO., LTD	Part of Nio Inc.

137	Chongqing Dadukou District Lixin Auto Parts Factory	No document available
138	Changzhou BYD Auto CO., LTD	Part of BYD Company Limited
139	Toyota Kirloskar Motor Private Limited	Part of Toyota Motor Corporation
140	FAW Toyota Motor CO., LTD	Part of Toyota Motor Corporation
141	Zamyad Company Public Joint Stock	No document available
142	Ferrari SPA	Part of Ferrari NV
144	Volkswagen Poznan SP ZOO	Part of Volkswagen Group
145	Koito Manufacturing CO., LTD	No document available
147	Sinotruck Jinan Truck Company Limited	Part of Sinotruck (Hong Kong) Limited
149	BYD Automobile CO., LTD Changzhou Branch	Part of BYD Company Limited
150	Renault Espana SA	Part of Renault
152	Mitsubishi Fuso Truck And Bus Corporation	Part of Daimler Truck AG
153	Automobile-Dacia SA	Part of Renault
154	Anhui Jianghuai Automobile Group Corp., LTD	No document available
155	Pars Khodro Company Public Joint Stock	No document available
157	Toyota Motor East Japan, Inc.	Part of Toyota Motor Corporation
158	Shaanxi Heavy Duty Automobile CO., LTD	Part of Weichai Power CO., LTD
159	Mercedes-Benz Manufacturing Hungary Korlatolt Felelossegu Tarsasag	Part of Mercedes-Benz Group AG
161	Toyota Motor Manufacturing France	Part of Toyota Motor Corporation
163	Wanxiang Group Corporation	No document available
164	United Automotive Electronic Systems CO., LTD	Part of Robert Bosch Gesellschaft mit Beschraenkter Haftung
166	Jiangling Motors Corporation Limited	Part of Jiangling Motors Group CO., LTS
168	Fuzhou BYD Industrial CO., LTD	Part of BYD Company Limited
171	Chery Commercial Vehicle (Anhui) CO., LTD	Part of Chery Automobile CO., LTD
173	Peugeot Citroen Mulhouse SNC	No document available
175	Mitsubishi Motors (Thailand) CO LTD	Part of Mitsubishi Motors Corporation
176	BMW Motoren GMBH	Part of Bayerische Motoren Werke AG
179	Volvo Group Belgium	Part of AB Volvo
181	Xiangfan Lingqi Machinery CO., LTD	No document available
182	Autoalliance (Thailand) CO LTD	Part of Ford Motor Company and Mazda Motor Corporation
184	BMW (UK) Manufacturing Limited	Part of Bayerische Motoren Werke AG
185	Xpeng Inc.	Already encountered
186	Volkswagen Navarra SA	Part of Volkswagen AG
187	FAW Toyota Motor (Chengdu) CO., LTD Changchun Fengyue Branch	Part of Toyota Motor Corporation and FAW Jiefang Automotive CO., LTD
188	Iveco Espana SL	Part of Iveco Group NV
189	Ugimag SA DE CV	No document available
191	FPT Industrial SPA O, Per Esteso, Fiat Powertrain Technologies Industrial SPA	Part of Iveco Group NV
193	Jiangling Motors CO., LTD Xiaolan Branch	Part of Jiangling Motors Group CO., LTS
196	Peugeot Citroen Sochaux SNC	Part of Stellantis NV
199	Panasonic Automotive Systems CO., LTD	Part of Panasonic Holdings Corporation

200	Zhengzhou BYD Auto CO., LTD	Part of BYD Company Limited
201	Daqing Volvo Car Manufacturing CO., LTD	Part of Volvo Car AB
202	FCA Poland SP ZOO	Part of Stellantis NV
203	Audi Brussels	Part of Audi AG
204	Volkswagen Autoeuropa, LDA	Part of Volkswagen AG
206	SAIC GM Dongyue Motors Company Limited	Part of SAIC Motor Corporation Limited and General Motors
207	Ningbo Hangzhou Bay Geely Automotive Parts CO., LTD	Part of Geely Holding Group
209	Deepal Blue Automotive Technology	Part of Chongqing Changan Automobile Company Limited
210	MAN Trucks SP ZOO	No document available
213	PCA Slovakia, SRO	Part of Stellantis NV
214	Societe Mecanique Automobile De L'est	No document available
215	Volkswagen Automatic Transmission (Tianjin) CO., LTD	Part of Volkswagen AG
217	Changan Ford Automobile CO., LTD	Part of Ford Motor Company
218	Beijing Hyundai Motor Company	Part of Hyundai Motor Company
219	Tri Petch Isuzu Sales CO LTD	Part of Isuzu Motors Limited
220	Northern Lingyun Industrial Group CO., LTD	No document available
224	Changsha Xingchao Auto CO., LTD	No document available
227	Denso Europe BV	Part of Dense Corporation
230	Vauxhall Motors Limited	Part of Stellantis NV
231	Toyota Motor Manufacturing (UK) Limited	Part of Toyota Motor Corporation
233	Magyar Suzuki Zartkoruen Mukodo Reszvenytarsasag	No document available
234	SAIC Maxus Automotive CO., LTD	Part of SAIC Motor Corporation Limited
236	Asia Euro Automobile Manufacturing (Taizhou) CO., LTD	Part of Volvo Car AB
238	Beijing Foton Daimler Automotive CO., LTD	Part of Daimler Truck AG
239	Automobili Lamborghini SPA	No document available
240	Horse Powertrain Spain SL	No document available
241	Dongfeng Commercial Vehicle CO., LTD	Part of Dongfeng Motor Group CO., LTD
242	Toyota Motor Manufacturing Czech Republic, SRO	Part of Toyota Motor Corporation
243	Societe Europeenne De Vehicules Legers Du Nord – Sevel Nord	Part of Stellantis NV
248	Ford Otosan Romania SRL	Part of Ford Motor Company
250	Zhongjia Automobile Manufacturing (Chengdu) CO., LTD	No document available
251	Renault Do Brasil LTDA	Part of Renault
252	Ford Motor Company (Thailand) CO LTD	Part of Ford Motor Company
253	Seres Auto CO., LTD	Part of Seres Group CO., LTD
255	Advics CO., LTD	No document available
256	Bosch Corporation	Part of Robert Bosch Gesellschaft mit Beschraenkter Haftung
257	Volvo Powertrain Aktiebolag	Part of Volvo AB

258	Mercedes-Benz Manufacturing Poland SP ZOO	Part of Mercedes-Benz Group AG
259	Schaeffler (China) CO., LTD	Part of Schaeffler AG
261	Robert Bosch France	Part of Robert Bosch Gesellschaft mit Beschraenkter Haftung
262	Mobis Automotive Czech SRO	Part of Hyundai Mobis CO., LTD
263	VDL Nedcar BV	Part of VDL Group
264	Societe Vehicules Automobiles Batilly	Part of Renault
265	Macheng Fudie Auto Parts CO., LTD	No document available
266	Peugeot Citroen Poissy SNC	Part of Stellantis NV
269	Ningbo Jirun Auto Parts CO., LTD	No document available
270	Hefei Changan Automobile CO., LTD	Part of Chongqing Changan Automobile CO., LTD
272	Forest River Inc	No document available
274	Djonson Meti Skopje Dooel	No document available
275	Shiyan Yunlihong Industry And Trade CO., LTD	No document available
276	Schmitz Cargobull Aktiengesellschaft	No document available
277	Autokiniton Global Group LP	No document available
278	Renault Korea Motors CO., LTD	Part of Renault
279	AISAN Europe	No document available
280	Dima Holdings CO., LTD	No document available
281	Amsted Industries Incorporated	No document available
282	Dongfeng Honda Engine CO., LTD	Part of Dongfeng Motor Group Company Limited and Honda Motor CO., LTD
283	Fiat India Automobiles Private Limited	Part of Stellantis NV

4.2 Data storage and processing

After selecting and storing the available annual reports, the number of documents in the folder consists of 125 annual reports. The data are stored as "nr. company name" (i.e. 1 Volkswagen AG.pdf). The annual reports are imported into R via this folder path. Using pdftools, the files and the texts are listed as objects. These objects provide a basis to transform the files, texts, and company names to a tidy format. This is executed via dplyr and tibble. Eventually, the data are stored according to the following format:

	file	text	company
1	1 Volkswagen AG.pdf	2023 ANNUAL REPORT ...	1 Volkswagen AG
2	10 Robert Bosch Gesellschaft Mit Beschraenkter Haftung.pdf	CROSSROADS Annual report 2023 02 Bosch is a nexus – a ...	10 Robert Bosch Gesellschaft Mit Beschraenkter Haftung
3	101 Autoliv, Inc.pdf	Annual and Sustainability Report 2023 ...	101 Autoliv, Inc
4	102 Rheinmetall AG.pdf	Titel KEY FIGURES 2023 | RHEINMETAL...	102 Rheinmetall AG
5	103 Dana Incorporated.pdf	2023 ANNUAL REPORT World In Motion About Dana Dana ...	103 Dana Incorporated

Figure 8, format data storage annual reports

After storing and formatting the annual reports data, the coding scheme (see Figure 7) is also stored as an object. In this list, each dimension is displayed with the corresponding operational indicators. Eventually, the coding scheme is stored according to the following format:

Name	Type	Value
coding_scheme	list [23]	List of length 23
autonomous_maintena...	character [3]	'operator ownership' 'production equipment' 'compliance'
focused_maintenance	character [4]	'16 losses' 'FMEA' 'system efficiency' 'OEE'
planned_maintenance	character [4]	'equipment life cycle' 'PM check sheets' 'MTBF' 'MTTR'

Figure 9, format data storage coding scheme

The next paragraph elaborates on the first exploratory insights created while applying the coding scheme to the annual reports data.

4.3 Exploratory analysis

The coding scheme is applied to the annual reports data using dplyr, stringr, and tidyverse. For each dimension of the coding scheme, the presence and the count in each report are checked. The results are stored in a table format, where the file, company name, text, presence of each dimension, and count of each dimension are displayed per annual report. A summary of the results was created by using dplyr, tidyr, and ggplot2. This led to the following first exploratory insight:

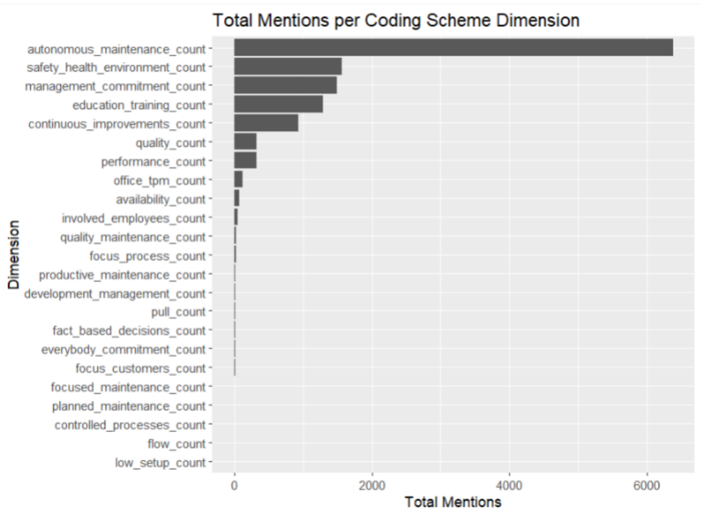

Figure 10, Exploratory analysis: Total Mentions per Coding Scheme Dimension

In addition to the general total mentions per coding scheme dimension, another first exploratory insight was created:

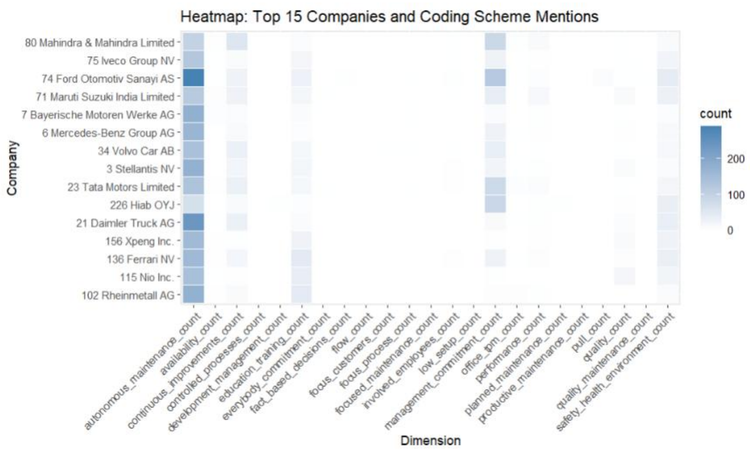

Figure 11, Exploratory analysis: Top 15 Companies and Coding Scheme Mentions

The two visuals provide an extra insight in addition to the coding results, namely which dimensions occur the most often and the companies with the most coding scheme mentions. These are valuable insights. However, the data and coding scheme are not validated. The next two paragraphs will elaborate on the validation process.

4.4 Dictionary validation

The first exploratory analysis was purely based on the coding scheme (see Figure 7). To validate this coding scheme, a comprehensive literature review is conducted. For each of the 23 coding scheme dimensions, ten different articles are obtained from the Scopus database. Based on the definition of the concerning dimension in each article, more operational indicators are collected to validate all dimensions. This led to a validated dictionary (see Appendix 1). The validated dictionary is stored in R as an object in the same way as the initial coding scheme. This looks like the following:

Name	Type	Value
coding_scheme_validated	list [23]	List of length 23
autonomous_maintena...	character [25]	'operator ownership' 'production equipment' 'compliance' 'repair equipment' 'cor ...
focused_maintenance	character [20]	'16 losses' 'FMEA analysis' 'system efficiency' 'OEE' 'small improvement' 'entir ...
planned_maintenance	character [27]	'equipment life cycle' 'PM check sheets' 'MTBF, MTTR' 'systematic maintenance' ' ...

Figure 12, format data storage validated coding scheme

To ensure eventual establishment of construct validity, the validated coding scheme is compared with English dictionaries using qdapDictionaries. The results show that 564 out of 591 indicators are not found in the English dictionary (95%). After splitting all phrases into individual words, 509 out of 570 indicators are found in the English dictionary (89%). The remaining 11% was not found. These overall results indicate a valid and specific dictionary based on theory. By splitting a phrases in individual words, the results show that the indicators are based on valid English words.

4.5 Data validation

Before applying the validated coding scheme to the data, a customized stop-word list is applied to the data (see Appendix 2). This stop-word list is based on the 50 most frequent occurring terms in the annual reports (i.e. "2023", "financial", "report") and standard stop-words from tidytext. Only the word "management" is excluded from the stop-word list as this is a relevant word in the dimensions and indicators. Eventually, the cleaned data looks like the following:

	file	company	text
1	1 Volkswagen AG.pdf	1 Volkswagen AG	key figures volkswagen 20221 volume data2 thousands deli...
2	10 Robert Bosch Gesellschaft Mit Beschraenkter Haftung.pdf	10 Robert Bosch Gesellschaft Mit Beschraenkter Haftung	crossroads 02 bosch nexus paths intersect disparate trends ...
3	101 Autoliv, Inc.pdf	101 Autoliv, Inc	sustainability 23 content autoliv glance 04 ceo message tran...
4	102 Rheinmetall AG.pdf	102 Rheinmetall AG	titel key figures | rheinmetall key figures 2021 2020 2019 20...
5	103 Dana Incorporated.pdf	103 Dana Incorporated	world motion dana dana leader design manufacture highly ...

Figure 13, format data storage cleaned and validated annual reports

After validation of the coding scheme, comparing it to an English dictionary, and cleaning and validating the annual reports data, the validated coding scheme is applied to the cleaned and validated data. This led to the following insights:

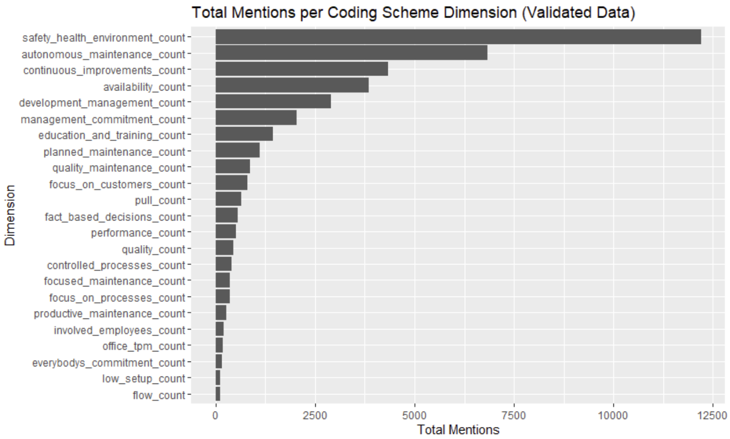

Figure 14, Total Mentions per Coding Scheme Dimension (Validated Data)

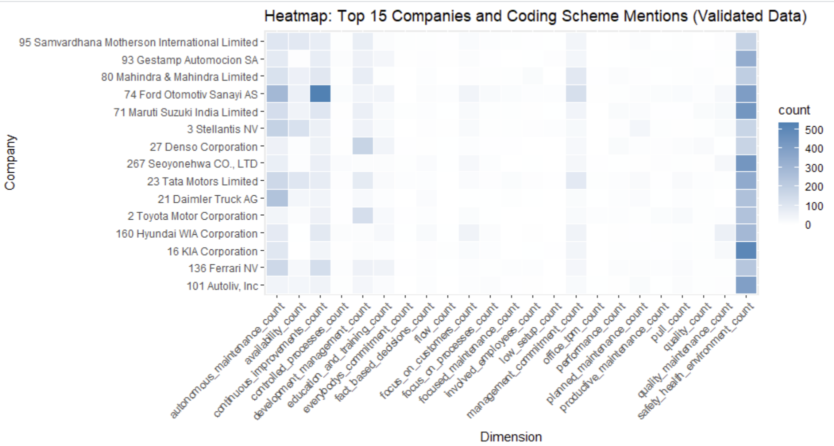

Figure 15, Top 15 Companies and Coding Scheme Mentions (Validated Data)

Validating the insight results back to original individual reports is fundamental in enhancing construct validity. Therefore, the top five companies, and top- and bottom dimensions are identified to execute this. To validate those results back to original individual reports, the KWIC (Keyword in Context) principle is applied to a random sample of the top- and bottom five dimensions and the dependent variables on the top 5 companies using dplyr and quanteda. Table 4 shows the results of the KWIC analysis.

Table 4. KWIC results on top 5 companies

Dimension:	**Precision:**
Safety, health and environment	0.74
Autonomous maintenance	0.42
Continuous improvements	0.84
Development management	0.72
Involved employees	0.78
Office TPM	0.67
Everybody’s commitment	0.74
Low setup	0.39
Flow	0.73
Availability	0.14
Performance	0.69
Quality	0.84

The KWIC analysis shows an average precision of 0.64. This means that 64% of the sample has a positive predicted value. In addition, the dimensions “Autonomous maintenance”, “Low setup”, and “Availability” are biased by the indicators “compliance”, “cost savings”, and “adjustment”. These results should be kept in mind when running and interpreting the output of the regression analysis.

Finally, the correlation between the obtained results and financial performance indicators is analysed to evaluate the extent to which the annual report content represents an organizational context. The results of this additional analysis is displayed in Table 5.

Table 5. Correlation analysis between obtained results and financial performance indicators

	ROCE	Asset Turnover Ratio	Net Profit Margin
Availability	0.16	-	-
Autonomous maintenance	-0.01	-	-
Focused maintenance	0.14	-	-
Planned maintenance	-0.12	-	-
Quality maintenance	0.02	-	-
Education and training	-0.05	-	-
Office TPM	-0.01	-	-
Development management	0.01	-	-
Safety, health and environment	0.23	-	-
Performance	-	-0.25	-
Pull	-	-0.01	-
Flow	-	0.18	-
Low setup	-	-0.03	-
Controlled processes	-	0.04	-
Productive maintenance	-	-0.06	-
Involved employees	-	0.04	-
Quality	-	-	0.05
Focus on customers	-	-	0.01
Management commitment	-	-	0.18
Everybody’s commitment	-	-	0.00
Focus on processes	-	-	0.23
Continuous improvements	-	-	0.15
Fact-based decisions	-	-	-0.05

The results show some meaningful correlations, for example Availability and ROCE (0.16), Focused maintenance and ROCE (0.14), and Quality and Net Profit Margin (0.05). This indicates that the annual report content represents an organizational context to a certain extent. However, the correlation between Performance and Asset Turnover Ratio seems to be negative (-0.25). As the KWIC analysis revealed a number of biased indicators and this correlation analysis indicates that not every dimension represents the organizational context as expected, this indicates that the processing and validation of the data involves implications that should be taken into account when interpreting the regression output.

4.6 Regression analysis

For each individual hypothesis, a regression analysis is conducted. In each analysis, the dependent variable concerns the specific OEE element count (availability, performance, or quality). As the total mentions per dimension vary in absolute numbers, the values in the regression analyses are standardized using z-scores. The results of the regression analyses are provided in Table 5, 6, and 7 respectively. Note that (1) concerns the initial linear regression model, (2) is about linear regression robustness tests by removing biased indicators, (3) reflects logistic regression robustness tests with binary presence independent variables, and (4) indicates logistic regression robustness tests with standardized count independent variables. Full results of the regression analyses, testing assumptions of the linear model, and robustness tests are included in Appendix 3.

Hypothesis 1 suggests that managerial actions with a higher degree of TPM positively impact the availability element of the OEE in global automotive production operations. The findings show the following output:

Table 6. Regression results hypothesis 1

	(1)	(2)	(3)	(4)
Total Productive Maintenance (TPM)				
Autonomous maintenance	0.2192*	-0.1495	-1.51581	-0.15136
	(0.036)	(0.206)	(0.10085)	(0.636)
Focused maintenance	0.4938***	0.1400	2.21411**	-0.22204
	(0.0001)	(0.196)	(0.00746)	(0.458)
Planned maintenance	0.1523	-0.01908	-1.80284	1.86783*
	(0.0622)	(0.857)	(0.20012)	(0.010)
Quality maintenance	-0.1963	-0.02742	0.04112	0.14920
	(0.8356)	(0.818)	(0.96830)	(0.685)
Education and training	-0.1774	0.1009	2.95690**	0.31773
	(0.0713)	(0.397)	(0.00810)	(0.419)
Office TPM	0.05073	0.04242	0.18184	-0.04224
	(0.5281)	(0.673)	(0.69997)	(0.875)
Development management	-0.09450	-0.04107	0.39456	0.11662
	(0.2771)	(0.713)	(0.61360)	(0.706)
Safety, health and environment	-0.1345	0.1468	-1.38976	0.23208
	(0.1950)	(0.236)	(0.44939)	(0.542)
R^2	0.4006	0.05561	-	-
F / Δ	9.189***	0.8096	16.65*	18.04*
	(0.0001)	(0.5955)	(0.034)	(0.021)
n of observations	119	119	119	119

The dependent variables concern the availability element of the OEE ((1) and (2) are linear regression, (3) and (4) are logistic regression)

The overall regression model is statistically significant ($F = 9.189$ and $p <.001$) and explains 40.06% of the variance in the dependent variable availability_count ($R^2 = 0.4006$). The estimated coefficients for autonomous_maintenance_count ($\beta = 0.219$, $p = 0.0306$) and focused_maintenance_count ($\beta = 0.494$, $p <.001$) are positive and significant. This indicates that the number of mentions of availability increase as a result of autonomous maintenance- and focused maintenance mentions. These results imply that managerial actions with a higher degree of TPM positively impact the availability element of the OEE in global automotive production operations, especially due to managerial actions aimed at autonomous maintenance and focused maintenance. Thus, hypothesis 1 is supported. However, these results should be interpreted with caution as autonomous maintenance and availability are biased by the indicators “compliance” and “adjustment(s)”.

Hypothesis 2 suggests that managerial actions with a higher degree of LM positively impact the performance element of the OEE in global automotive production operations**.** The findings show the following output:

Table 7. Regression results hypothesis 2

	(1)	(2)	(3)	(4)
Lean Management (LM)				
Pull	0.2798**	0.2804**	1.4043*	0.582958
	(0.00812)	(0.00899)	(0.0480)	(0.1419)
Flow	-0.08567	-0.03813	0.3268	0.074673
	(0.40881)	(0.70173)	(0.5687)	(0.8580)
Low setup	0.1226	-0.02338	-0.2366	0.008438
	(0.20488)	(0.79988)	(0.7827)	(0.9851)
Controlled processes	-0.008003	-0.02264	-0.1461	0.076293
	(0.94518)	(0.84631)	(0.8411)	(0.8669)
Productive maintenance	-0.03128	-0.03131	0.5155	0.171555
	(0.78934)	(0.79146)	(0.4264)	(0.7071)
Involved employees	0.1561	0.1787	1.3217*	1.307007
	(0.11646)	(0.07289)	(0.0262)	(0.0931)
R^2	0.1263	0.1142	-	-
F / Δ	2.699*	2.406*	14.482*	12.14
	(0.01742)	(0.03177)	(0.025)	(0.059)
n of observations	119	119	119	119

The dependent variables concern the performance element of the OEE ((1) and (2) are linear regression, (3) and (4) are logistic regression)

The overall regression model is statistically significant ($F = 2.699$, $p = 0.01742$) and explains 12.63% of the variance in the dependent variable performance_count ($R^2 = 0.1263$). Only the estimated coefficient of pull_count ($\beta = 0.2798$, $p = 0.00812$) is positive and significant. This indicates that number of mentions of performance increases as a result of pull mentions. These results imply that managerial actions with a higher degree of LM positively impact the performance element of the OEE in global automotive production operations, especially due to managerial actions aimed at pull. Thus, hypothesis 2 is supported. However, these results should be interpreted with caution as low setup is biased by the indicator “cost savings”.

Hypothesis 3 suggests that managerial actions with a higher degree of TQM positively impact the quality element of the OEE in global automotive production operations. The findings show the following output:

Table 8. Regression results hypothesis 3

	(1)	(2)	(3)	(4)
Total Quality management (TQM)				
Focus on customers	0.002791	0.002791	0.15250	-1.2321
	(0.9841)	(0.9841)	(0.8570)	(0.0775)
Management commitment	0.09236	0.09236	0.05957	0.6778
	(0.4782)	(0.4782)	(0.9590)	(0.3424)
Everybody's commitment	0.2000*	0.2000*	1.02699	0.4957
	(0.0255)	(0.0255)	(0.0797)	(0.4622)
Focus on processes	0.2097	0.2097	0.60665	0.4298
	(0.1075)	(0.1075)	(0.3136)	(0.3641)
Continuous improvements	0.03506	0.03506	15.86897	1.5939
	(0.7978)	(0.7978)	(0.9909)	(0.1725)
Fact based decisions	0.0285	0.0285	1.66989*	2.0410*
	(0.8156)	(0.8156)	(0.0106)	(0.0114)
R^2	0.1451	0.1451	-	-
F / Δ	3.169**	3.169**	24.16***	27.195***
	(0.006564)	(0.006564)	(0.0005)	(0.0001)
n of observations	119	119	119	119

The dependent variables concern the quality element of the OEE ((1) and (2) are linear regression, (3) and (4) are logistic regression)

The overall regression model is statistically significant ($F = 3.169$, $p = 0.006564$) and explains 14.51% of the variance in the dependent variable quality_count ($R^2 = 0.1451$). Only the estimated coefficient of everybodys_commitment_count ($\beta = 0.2$, $p = 0.0255$) is positive and significant. This indicates that the number of mentions of quality increases as a result of everybody's commitment mentions. These results imply that managerial actions with a higher degree of TQM positively impact the quality element of the OEE, especially due to managerial actions aimed at everybody's commitment. Thus, hypothesis 3 is supported.

4.7 Robustness tests

As the regression models indicate, each individual model supports the hypothesis of the concerning theorized managerial actions positively impacting the specific OEE element. To investigate the robustness of the findings, several models are re-estimated. First, the biased indicators "compliance", "cost savings", and "adjustment(s)" are removed from the coding scheme. This robust coding scheme is re-applied to the data. Second, logistic regression models using binary presence variables as the independent variables are re-estimated. Third, logistic regression models are re-estimated, using standardized count variables as independent variables. The outputs are presented in Table 5, 6, and 7.

After removing the biased indicators "compliance" and "adjustment(s)", the overall model is statistically insignificant ($F = 0.8096$, $p = 0.5955$) and explains 5.561% of the variation in the dependent variable availability_count ($R^2 = 0.05561$), thus not supporting hypothesis 1. Also, none of the independent variables show a positive and significant coefficient. This indicates that these biased indicators strongly affect the initial model. The second robustness test shows a statistically significant reduction of the null deviance compared with the residual deviance ($\Delta = 16.65$, $p = 0.034$), based on a Chi-square test. This model shows positive and significant coefficients of focused_maintenance_true ($\beta = 2.21411$, $p = 0.00746$) and education_and_training_true ($\beta = 2.95690$, $p = 0.00810$). This means that it is likely that availability mentions are present as a result of the presence of focused maintenance and education and training mentions. The third robustness test also shows a statistically significant reduction of the null deviance compared with the residual deviance ($\Delta = 18.04$, $p = 0.021$), based on a Chi-square test. This model shows a positive and significant coefficient of planned_maintenance_count ($\beta = 1.87683$, $p = 0.010$). This implies that it is likely that availability mentions are present due to increasing mentions of planned maintenance.

After removing the biased indicator "cost savings", the overall model remains statistically significant ($F = 2.406$, $p = 0.03177$) and explains 11.42% of the variance on the dependent variable performance_count ($R^2 = 0.1142$). Thus, the overall model still supports the hypothesis. Also, pull_count still shows a positive and significant coefficient ($\beta = 0.2804$, $p = 0.00899$). This means that it is still likely that the number of mentions of performance increases as a result of pull mentions after removing the biased indicator. The second robustness test shows a statistically significant reduction of the null deviance compared with the residual deviance ($\Delta = 14.482$, $p = 0.025$), based on a Chi-square test. Also, the model shows positive and significant coefficients of pull_true ($\beta = 1.4043$, $p = 0.0480$) and involved_employees_true ($\beta = 1.3217$, $p = 0.0262$). This means that it is likely that performance mentions are present as a result of the presence of pull and involved employee mentions. The third robustness test shows a statistically insignificant reduction of the null deviance compared with the residual deviance ($\Delta = 12.14$, $p = 0.059$), based on a Chi-square test. Also, none of the independent variables show a positive and significant coefficient, thus not supporting the hypothesis.

The regression model regarding the third hypothesis did not contain biased indicators. Based on the robust coding scheme, the model output shows the same results as expected. The second robustness test shows a statistically significant reduction of the null deviance compared with the residual deviance ($\Delta = 24.16$, $p = 0.0005$), based on a Chi-square test. Also, the model shows a positive and significant coefficient of fact_based_decisions_true ($\beta = 1.6699$, $p = 0.0106$). This means that it is likely that quality mentions are present as a result of the presence of fact based decisions mentions. The third robustness test also shows a statistically significant reduction of the null deviance compared with the residual deviance ($\Delta = 27.195$, $p < .001$), based on a Chi-square test. Fact_based_decision_count shows a positive and significant coefficient ($\beta = 2.0410$, $p = 0.0114$), implying that it is very likely that quality mentions are present due to increasing mentions of fact based decisions.

The robustness tests accounted for model deviations in different situations by removing the biased indicators, testing logistic regression with binary presence variables as independent variables, and testing logistic regression with standardized count variables as independent variables. From the robustness tests regarding hypothesis 1, two out of three show a statistically significant overall model. Moreover, focused maintenance shows a positive and significant coefficient on the dependent variable across different models. Autonomous maintenance, planned maintenance, and education and training show a positive and significant coefficient on the dependent variable in one of the models. From the robustness tests regarding hypothesis 2, two out of three show a statistically significant overall model. Moreover, pull shows a positive and significant coefficient on the dependent variable across different models. Involved employees shows a positive and significant coefficient on the dependent variable in one of the models. From the robustness tests regarding hypothesis 3, all three show a statistically significant overall model. Moreover, everybody’s commitment and fact based decisions show a positive and significant coefficient on the dependent variable across different models.

5. Discussion

Existing literature shows that prediction models can significantly enhance crucial KPIs like the OEE in an advanced automotive industry setting. The next challenge here is to implement a model that can predict the effect of managerial actions on production management. As the prediction of the OEE could only give the holistic performance of production operations, understanding whether managerial actions have a positive or negative impact on detailed elements of production operations in the automotive industry is of critical importance (Ayadi et al., 2023; Mjimer et al., 2022). Therefore, this empirical analysis aimed to develop a framework that can predict whether managerial actions have a positive or negative impact on detailed OEE elements of production operations in the global automotive industry. This innovative approach involves several implications, especially with regards to reflecting the intended measurements. The keyword into context analysis and the additional correlation analysis clearly indicate this. Even though a comprehensive and theoretically grounded validation process is conducted, experience learns that representing the intended measurement remains a complex and not straightforward process. Nevertheless, the empirical analysis contributed to supporting the hypotheses regarding the positive impact of managerial actions theorized within TPM, LM, and TQM on respectively the availability, performance, and quality elements of the OEE. However, one should interpret these results with nuance, as the introduction of this innovative method involves a number of implications. The next three paragraphs will discuss the initial theory, interpretation of the empirical results, and a reflection on how these findings support the hypotheses and underlying theory. Moreover, it discusses the theoretical and practical implications with regards to each hypothesis.

According to hypothesis 1, managerial actions with a higher degree of TPM positively impact the availability element of the OEE in global automotive production operations. Sumasto et al. (2024) argues that the availability rate is a ratio showing the utilisation of time available for machine or equipment operation, thus indicating effectiveness. The TPM approach optimizes this equipment effectiveness, eliminates breakdowns and promotes autonomous maintenance (Ahuja & Khamba, 2008; Bhadury, 2000). Thus, this supports that managerial actions with a higher degree of TPM positively impact this availability rate. The initial empirical results show that this statement is supported by a statistically significant overall model, with autonomous maintenance and focused maintenance as positively significant predictors. However, when removing biased indicators “compliance” and “adjustment(s)” in a robustness test, the model becomes insignificant and no independent predictor is contributing significantly anymore. Conducting robustness tests with logistic regression, both models indicate a statistically significant relationship. In the logistic regression with binary presence variables as predictors, focused maintenance again indicates a positive and significant coefficient. The relationship between TPM and availability seems to be positive, but this study shows some inconsistencies across different models and situations. The biggest inconsistencies arise when removing the biased indicators based on the KWIC analysis. Moreover, the correlation analysis between the obtained results and the ROCE implies that determination whether the annual report content represents an organizational context is challenging. Chaurey et al. (2023) confirms this issue by stating that TPM is not a simple, but very complex concept. It is hard to understand different stakeholder views towards TPM implementation. Hence, the development of operational indicators of TPM based on literature can cause inconsistencies. This study contributes towards a better understanding of the TPM concept. The validated dictionary based on a systematic literature review captures underlying indicators that reflect TPM and its dimensions. Also, the empirical analysis showed that the theorized operational indicators were matched to keywords in a different context. This emphasizes the complex nature of the theoretical concept of TPM. Managerial implications concern the effective implementation of TPM to optimize equipment effectiveness. Automotive managers can think of implementing focused maintenance practices in a systematic and methodological way by aiming for small improvement and involving the entire workforce.

Regarding hypothesis 2, it was suggested that managerial actions with a higher degree of LM positively impact the performance element of the OEE in global automotive production operations**.** The main objective of LM as a socio-technical system is to eliminate waste. One type of waste reduction that LM aims to reduce is speed loss. The performance element of the OEE measures those speed losses in terms of interruptions or temporary malfunction, and speed loss from reduced run rates. As the performance rate measures the ability of equipment or machinery to produce products in percentages, these arguments support the hypothesis (Shah & Ward, 2007; Sumasto et al., 2024; Trattner et al., 2020). The initial empirical results build up on this foundation by indicating a statistically significant overall model, with pull as positive significant predictor. Testing robustness by removing the biased indicator “cost savings”, the model remains significant with pull as the only positive significant predictor. Additional robustness testing with logistic regression strengthens this by also showing the same result with binary presence variables as predictors. Regarding the logistic regression with binary presence variables, pull still shows the only positive significant coefficient. Only the logistic regression with count variables as predictors indicates an insignificant overall model. When analysing the correlation between the obtained results and the Asset Turnover Ratio, the pull dimension and performance element show a negative correlation in relation to the Asset Turnover Ratio. This study shows that the relationship between LM and performance is positive and quite robust, especially regarding indicators related to the pull dimension. However, one cannot fully determine whether these numbers exactly represent an organizational context. Nevertheless, these findings support the theory as firms use pull production to produce the units needed, at the time needed, and in the quantities needed. Hence, increasing the ability of equipment or machinery to produce products in percentages (Shah & Ward, 2007). The results theoretically contribute to the understanding of the LM dimensions and the robust effect of pull practices on the performance element of the OEE. Also, it contributes by emphasizing a critical attitude regarding the operationalization of low setup. Practical implications of this study are the need for automotive production managers to apply pull production practices. Implementing this philosophy, materials are provided just in time by the advancement of workflows based on timing and readiness of the next stage. Tools like a kanban are helpful to implement such practices to ensure that highly customizing customer expectations are met.

Hypothesis 3 suggested that managerial actions with a higher degree of TQM positively impact the quality element of the OEE in global automotive production operations. The main goal of TQM is to produce against quality standards and reduce quality defects (Hellsten & Klefsjö, 2000). Regarding these standards and defects, the quality element of the OEE expresses these factors as the total output minus defect output in a percentage of the total output (Hellsten, 1997; Olalere & Ramdass, 2024). Producing against quality standards and reducing quality defects will increase this percentage, thus supporting the hypothesis. The initial empirical model follows up this statement by showing a statistically significant overall model. Everybody's commitment contributes here as a significant predictor. As there were no biased indicators involved, the first robustness test shows the same results with everybody's commitment as significant predictor again. The robustness tests with both the logistic regression models indicate a robust and significant relationship. Fact based decisions shows a robust positive and significant coefficient, thus contributing as predictor to the hypothesis. As there were no biased indicators involved, the context of where the keywords were obtained did not play a significant role. Moreover, the correlation between the quality element and the Net Profit Margin is slightly positive. Still, everybody's commitment and fact-based decisions show no and a negative correlation respectively. This indicate that one should interpret the empirical results with caution as it is questionable if those numbers represent an organizational context. From a theoretical perspective, Yusr et al. (2017) emphasizes the critical importance of fact based decisions by arguing that decision making should be based on factual and reliable information. As decision making is a crucial task for top management, this is a relevant factor in improving the quality rate by producing against quality standards and reduce quality defects. Managers should use approaches as TQM and use models to plan steps for continuous development. As there are many vague descriptions and few definitions of what TQM really is, this study contributes to theory by showing the effect of TQM on the quality element of the OEE on dimension level (Hellsten & Klefsjö, 2000). The empirical results imply what exact practices and indicators of TQM have strong and robust effects on the quality rate. Practically, this study contributes by emphasizing the importance of fact based decisions by management to improve the quality element of the OEE. For automotive managers, this means that the use of models and tools like statistical process control and design of experiments are the most effective in implementing a strategy regarding continuous development.

This study provides empirical support for the positive impact of managerial actions with a higher degree of TPM, LM, TQM on availability, performance, and quality of the OEE. The developed predictive framework enables a systematic method to assess the impact of managerial actions on OEE elements in global automotive production operations. However, the study faces a number of implications when interpreting the empirical results. The results are affected by the context where the keywords were obtained. This is explicitly shown by removing the biased indicators "compliance" and "adjustment(s)". In addition, the results are also challenged by the extent to which the obtained numbers represent an organizational context. The correlation analysis with financial performance indicators indicates this. Theoretically, this study contributes by a validated set of dimensions and indicators of theory based management practices. In addition, it shows the most significant and robust dimensions positively impacting OEE elements. Practically, this study provides which managerial actions are the most effective and robust in improving OEE elements in global automotive production operations. However, this study also involved challenges and limitations. The next paragraph will elaborate on these limitations and provide opportunities for future research.

6. Conclusion

6.1 Conclusion

For a sample of global automotive firms, this study assesses the impact of managerial actions on OEE elements. The results indicate a positive effect of managerial actions with a higher degree of TPM, LM, and TQM on respectively availability, performance, and quality of the OEE. However, these results should be interpreted with nuance as some the effects are not that consistent across different models. The robustness tests show deviations because of removing biased indicators and the different context of logistic regression. In particular, this is the case for the impact of managerial actions with a higher degree of TPM on the availability element of the OEE. This is the first study that develops a predictive framework to assess the impact of managerial actions on detailed OEE elements of production operations in the global automotive industry. Practically, the most effective and robust managerial actions to improve OEE elements in this automotive setting have been identified. The next paragraphs will elaborate on the limitations of this study and opportunities for future research.

6.2 Limitations

Despite filling a gap in literature, this study is subject to several limitations. First, the use of annual reports data as source data introduces a possible limitation. As companies report their competence themselves, objective assessment may not be fully achieved. This indicates that the results obtained by the text mining process may be biased. Second, although the study provides a comprehensive operationalization via the coding scheme and ensures validation through a comprehensive literature review and keyword into context analysis, it is difficult to fully deal with the objective that all extracted text mining counts represent the intended measure intentions. This may still lead to biased measurement because of context sensitivity. Lastly, this study provides a comprehensive and transparent validation process. However, in obtaining operational indicators from collected definitions and analysing the keywords into context, manual judgement is not preventable. Therefore, the validation process is exposed to a degree of subjectivity. The mentioned limitations should be taken into account when interpreting the results of the predictive framework.

6.3 Future research

Future research could consider the enhancement of construct validity by applying advanced techniques like BERT or Word2Vec to better capture the semantics and contextual meaning of keywords related to managerial actions. In addition, future studies could focus on developing more robust classification or regression algorithms by expanding the sample size and dataset over multiple years. This enhances the process of assessing the impact of managerial actions on production operations in the global automotive industry via automation and robustness. Finally, seen the general and self-reported nature of annual report data, future work could conduct a case study at company level relying on the predictive framework. In this way, the results could be triangulated and further developed to better understand the nuances of the influence of managerial actions on OEE elements in a physical company setting.

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Appendix

Appendix 1: Validated dictionary

Dimension:	**Indicators:**
Autonomous maintenance	"operator ownership", "production equipment", "compliance", "repair equipment", "corrective action", "improvement strategies", "operator skills", "equipment perspective", "shop floor", "increment", "autonomous checking", "maintenance standards", "operator responsibility", "minor maintenance tasks", "standardization", "basic conditions", "deterioration", "visual control", "equipment maintenance", "routine maintenance", "own equipment", "proactive maintenance", "preventative maintenance", "special training", "repetitive downtime"
Focused maintenance	"16 losses", "FMEA analysis", "system efficiency", "OEE", "small improvement", "entire workforce", "continuous execution", "employee involvement", "methodical approach", "system problems", "cost effective", "time saving", "system optimization", "decreasing losses", "operational efficiency", "equipment effectiveness", "waste elimination", "improve performance", "standard operational procedure", "work instructions"
Planned maintenance	"equipment life cycle", "PM check sheets", "MTBF, MTTR", "systematic maintenance", "equipment reliability", "unplanned stoppages", "preventive maintenance", "corrective maintenance", "maintenance prevention", "machine breakdown", "machine malfunction", "routine maintenance", "reduce maintenance", "historical equipment failure", "equipment stoppages", "predicted failure rates", "measured failure rates", "equipment planning", "downtime reduction", "planned maintenance program", "periodic checkup", "predictive maintenance", "failure analysis", "equipment conditions", "preventive check", "replacement", "repair"
Quality maintenance	"zero defects", "equipment problems", "root causes", "3M conditions", "quality control", "product quality", "customer satisfaction", "control conditions", "machine conditions", "delighting customers", "high quality", "defect free manufacturing", "eliminate defects", "equipment conditions", "good working conditions", "high quality products", "faultless manufacturing", "process control system", "equipment availability", "improved manufacturing processes", "high quality production", "high production standards", "strict conditions", "prevent defects"
Education and training	"technological", "quality control", "interpersonal skills", "multi-skilling", "awareness training", "operator role", "equipment handling", "employee knowledge", "self learning", "daily maintenance", "optimal operating condition", "production personnel", "maintenance personnel", "employee performance", "general education", "TPM program", "technical training", "skills and abilities", "maintain/operate equipment", "equipment life span", "diverse skills", "actively engage", "self-sufficient maintenance", "operator skills", "operator ownership",

	"increasing skills", "maintenance skills", "operations skills", "periodic evaluation"
Office TPM	"synergy", "cost-related issues", "5S", "company meeting", "overall productivity", "job/role distribution", "follow up", "administrative functions", "functional loss", "efficient offices", "service provision", "production support", "administrative tasks", "streamlining processes", "efficiency spread", "all business operations", "manufacturing strategy", "master plan", "training plans", "business functions", "procedural hassle", "automated processes", "eliminating losses", "technical functions", "office automation", "eliminate losses"
Development management	"new equipment", "transforming systems", "maintenance improvement", "administrative tasks", "support production", "continuous development", "initiatives", "new equipment designs", "maintaining existing equipment", "new machinery", "lead time reduction", "raising overall output", "5S", "downtime duration", "maintenance handling", "MTTR", "practical knowledge", "design improvement", "existing equipment", "equipment maintenance", "strategy alignment", "TPM objectives", "advanced technologies", "proprietary equipment"
Safety, health and environment	"safe working environment", "incidents, injuries, accidents", "standard procedures", "personal protection", "environmental hygiene", "awareness among employees", "safety, health, environment", "safe workplace", "undamaged environment", "accidents", "occupational diseases", "environmental accidents", "safety", "health", "environment protection", "environmentally conscious", "healthy", "zero accidents", "zero pollution cases", "standard operating procedures", "surrounding area", "zero health damage", "zero fires", "zero pollution", "danger prevention"
Pull	"just in time production", "kanban", "pull production", "inventory levels", "just in time", "excess consumption", "waste reduction", "reorder point", "consumption trigger", "workflow advancement", "customer pull", "pull approach", "downstream", "one-by-one flow", "requesting customer", "zero inventory", "production line", "inventory costs", "customer demand", "single item costs", "customer value", "lead time", "buildability", "production needs", "required function", "trigger workstations", "kanban system", "material consumption", "downstream stage"
Flow	"continuous flow", "workflow optimization", "SMED", "information transfer", "data management", "mapping of the production process", "material movement", "material storage", "needed material", "product range selection", "station number calculation", "employee number calculation", "machinery layout planning", "workstation layout", "technological operations", "production equipment arrangement", "time frame production", "one piece flow", "single stage production", "flow management", "production runs", "coordination effort", "production lot size", "single suppliers", "material flow", "layout design", "production timing", "distribution timing", "process interruptions", "lean production system"

Low setup	"downtime reduction", "changeover time", "setup time reduction", "batch size", "cost savings", "production operations realization", "replacing tools", "machine preparation", "production activity", "previous lot", "subsequent lot", "single minute exchange of die", "single digit", "system downtime", "standardised setup", "mistake-free", "efficient setup", "sustainable setup", "setup changes", "production time losses", "levelled flow", "change machines", "group of different parts", "manufacturing lots", "reduce setup times", "lower lot sizes", "jit production", "reducing setup times", "production setup time reduction"
Controlled processes	"statistical process control", "defect free units", "production consistency", "statistical techniques", "process method", "production method", "production quality", "process management", "control chart", "statistical significance", "statistical tools", "further improvement", "process optimization", "minimizing variation", "process defects", "dmaic", "repetitive process", "stable process", "bottom line impact", "continuous improvement", "sustainable improvement", "process error", "waste reduction", "statistical analysis", "lean approaches", "process control", "visual control"
Productive maintenance	"address equipment downtime", "equipment availability", "preventive maintenance", "equipment downtime", "machinery breakdown", "production delay", "lead time", "equipment efficiency", "equipment lifespan", "manufacturing productivity", "processing steps", "environmental performance", "production stability", "controlled proces", "proper quality product", "low production cost", "machine reliability", "downtime reduction", "waste reduction", "lean manufacturing system", "enhance production", "machine efficiency", "device efficiency", "equipment effectiveness", "equipment lifetime", "involving everyone", "effectiveness prediction", "all maintenance activities", "effectiveness evaluation", "machine maintenance", "deferred maintenance", "production yield"
Involved employees	"employee involvement", "problem solving", "cross functional", "empowering employees", "working in teams", "process improvement", "receive feedback", "work teams", "exercise continuous improvement", "employee autonomy", "improvement specialists", "strategy understanding", "motivate employees", "company commitment", "direct participation", "mission fulfillment", "meet objectives", "employee application", "motivated workers", "efficient workers", "each organizational level", "knowledge sharing", "improving processes", "trained workers", "skillful employees", "exceptional people", "exceptional teams", "company philosophy", "employee respect", "decision making involvement", "learning opportunity", "all employees", "lean implementation"
Focus on customers	"customer surveys", "quality function deployment", "customer driven", "customer satisfaction", "customer needs", "customer requirements", "customer expectations", "customer priorities", "market focus", "internal customer needs", "external customer needs", "quality test by

	customer", "customer relations", "market researches", "customer centric strategy", "growth objective", "customer focused management", "waste reduction", "continuous improvement", "employee morale", "customer delivery", "customer viewpoint", "fit for purpose", "receive feedback"
Management commitment	"organizational culture", "leadership", "strategic quality", "shared vision", "clear goal", "support to employees", "quality management system", "management vision", "leadership commitment", "strategic direction", "foresight vision", "leadership exhibition", "management commitment", "employee empowerment", "total quality system", "employee involvement", "continuous improvement", "refined quality", "communication of goals", "resource provision", "employee motivation", "leadership ability", "inspire and motivate", "organizational objectives", "understanding employees", "employee satisfaction", "resource allocation", "motivating employees", "quality practices", "direct participation", "high level officials", "critical aspects"
Everybody's commitment	"improvement groups", "quality circles", "specific tools", "total commitment", "employee groups", "problem solving approaches", "employee involvement", "employee empowerment", "performance appraisal", "teamwork", "everybody's participation", "everybody in the company", "accomplish transformation", "open organization", "lean staff", "empowered work teams", "horizontal communication", "cross-functional teamwork", "organizational innovation", "people-centred culture", "flexible culture", "worker involvement", "real-time problem solving", "worker flexibility", "group culture", "everyone's voice", "results responsibility", "employee contribution", "quality improvement process"
Focus on processes	"process management", "control charts", "process maps", "ISO certification", "dashboard", "process metrics", "process effectiveness", "process efficiency", "product results", "customer oriented process", "focus on processes", "customer value creation", "focus on core processes", "customer focus", "process understanding", "systematic processes", "process operating costs", "customer requirements", "process improvement", "process discovery", "process monitoring", "key performance indicator", "data management", "improved outcomes", "streamlined processes", "process optimization", "process control"
Continuous improvements	"continuous improvement", "six sigma", "learning", "defect reduction", "organizational change", "innovation", "high quality products", "customer satisfaction", "cost reduction", "management practices", "waste elimination", "everyone involved", "creative approach", "using opportunities", "continuous learning", "improve products", "improve services", "improve processes", "kaizen", "raising output", "cutting waste", "streamlining operations", "organization's competitiveness", "human resource improvement", "environment improvement", "customer expectations", "transparant processes", "implementing solutions", "client satisfaction", "ongoing quality improvement", "business position", "reducing costs", "quality improvement"

Fact-based decisions	"statistical process control", "data-driven decisions", "design of experiments", "factual information", "reliable information", "continuous development", "process management", "pdca", "systematic processes", "explicit processes", "factual indicators", "process analysis", "process improvement", "statistical methods", "measurement standards", "statistical techniques", "quality strategy", "machinery control", "production control", "process capability", "product design", "manufacturing variation", "performance measurement", "business performance", "effective management", "quality control", "sampling techniques", "results-oriented", "customer value", "company performance"
Availability	"breakdowns", "downtime", "operating time", "loading time", "system operation", "breakdown", "system stoppages", "equipment failure", "breakdown losses", "setup time", "equipment adjustment", "time of operation", "time of loading", "set-ups", "adjustments", "other stoppages", "machine availability", "uptime", "tool service", "job change", "set-up", "adjustment", "downtime losses", "equipment availability", "actual operating time", "die changing", "machine running", "time lost", "equipment losses", "setup losses"
Performance	"speed loss", "interruption", "temporary malfunction", "output", "cycle time", "operating time", "production interruption", "equipment design speed", "actual operating speed", "speed losses", "performance efficiency", "machine idling", "work unit effectiveness", "production time", "maximum throughput", "equipment performance", "qualified production", "production deviation", "ideal cycle time", "actual production", "processed amount", "interrupted production", "quantity produced", "operating speed", "ideal speed", "idling", "products produced", "actual runtime", "equipment speed", "scheduled production time", "nominal capacity"
Quality	"quality loss", "quality standards", "quality defects", "output", "defect output", "total production", "defect amount", "machine startup", "reduced yield", "machine start up", "machine stabilisation", "effective production", "actual production", "quality losses", "equipment upstream", "quantity produced", "parts rejected", "good quantity", "produced quantity", "processed amount", "malfunctioning production equipment", "defect losses", "rework", "start-up", "produced items", "product specifications", "rejected components"

Appendix 2: Customized stop-word list

```
custom_stopwords <- c("2023", "financial", "company", "2022", "31", "report", "assets", "1",
"business", "board", "december", "statements", "income", "cash", "total", "2", "million", "tax",
"consolidated", "shares", "net", "information", "risk", "sales", "annual", "related", "share",
"3", "amount", "liabilities", "vehicles", "period", "based", "directors", "corporate", "equity",
"current", "loss", "development", "term", "including", "limited", "services", "market", "notes",
"capital", "fair", "vehicle", "future")
```

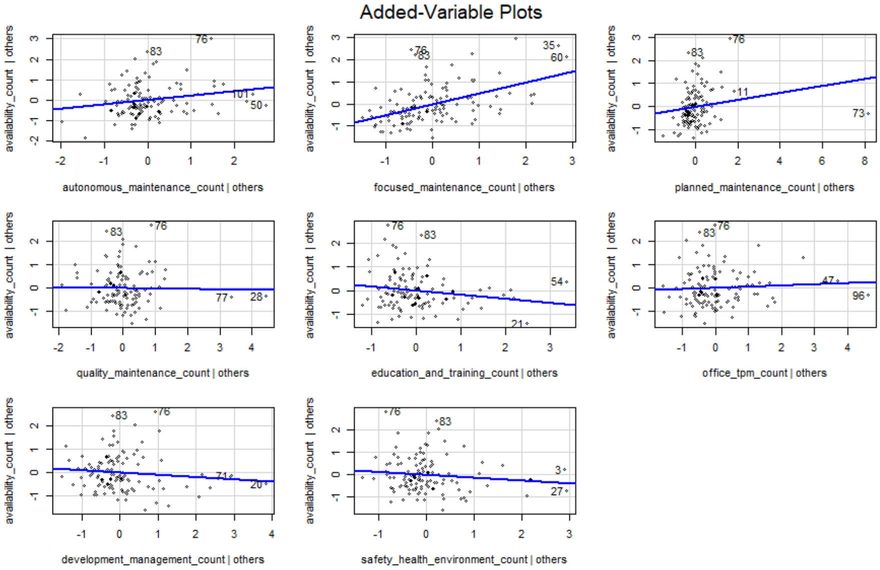
Appendix 3: Full regression analyses

H1: TPM→ availability

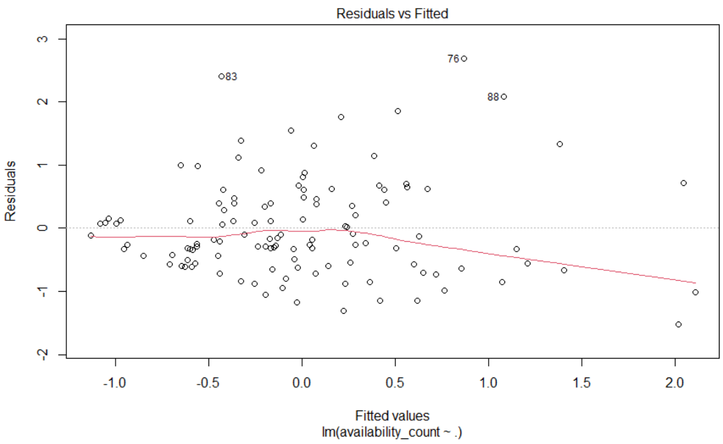
Baseline model

```
Call:
lm(formula = availability_count ~ ., data = model1_std)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.5211 -0.5531 -0.1624  0.3973  2.6865 

Coefficients:
                                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)                     -4.142e-18  7.351e-02   0.000   1.0000    
autonomous_maintenance_count     2.192e-01  1.001e-01   2.190   0.0306 *  
focused_maintenance_count        4.938e-01  8.672e-02   5.694 1.05e-07 ***
planned_maintenance_count        1.523e-01  8.086e-02   1.884   0.0622 .  
quality_maintenance_count       -1.963e-02  9.436e-02  -0.208   0.8356    
education_and_training_count    -1.774e-01  9.742e-02  -1.821   0.0713 .  
office_tpm_count                 5.073e-02  8.016e-02   0.633   0.5281    
development_management_count    -9.450e-02  8.651e-02  -1.092   0.2771    
safety_health_environment_count -1.345e-01  1.031e-01  -1.304   0.1950    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8019 on 110 degrees of freedom
Multiple R-squared:  0.4006,	Adjusted R-squared:  0.357 
F-statistic: 9.189 on 8 and 110 DF,  p-value: 1.282e-09
```

Checking Assumptions: Linear relationship



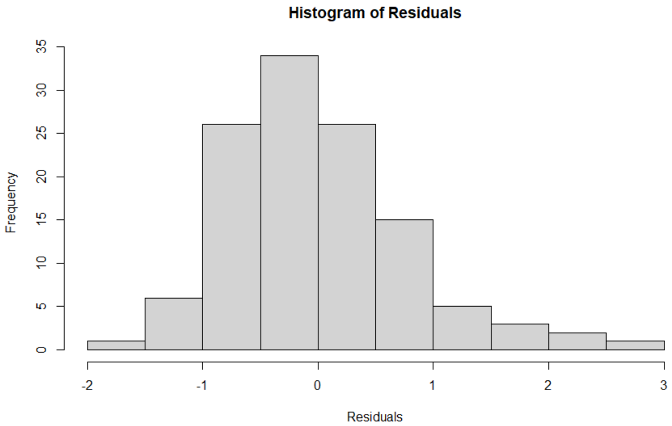
Checking Assumptions: Constant variance / uncorrelated error term

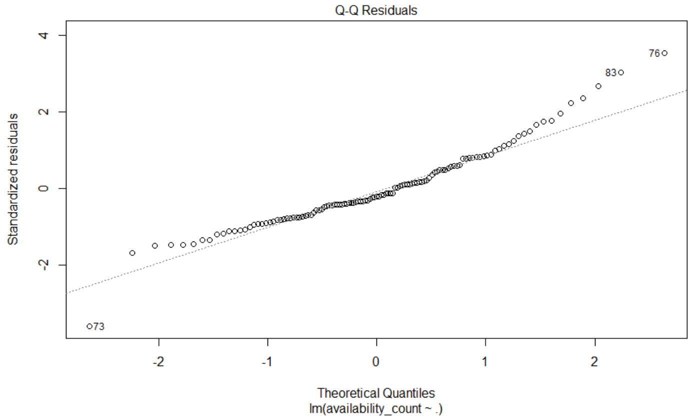


Checking Assumptions: No perfect multicollinearity (VIF)

```
  autonomous_maintenance_count        focused_maintenance_count        planned_maintenance_count
                      1.837706                         1.380108                         1.199856
     quality_maintenance_count     education_and_training_count                 office_tpm_count
                      1.633852                         1.741472                         1.179193
  development_management_count safety_health_environment_count
                      1.373386                         1.951659
```

Checking Assumptions: Normality of the error term





Robustness test 1: linear regression model (robust version)

```
Call:
lm(formula = availability_count ~ ., data = model1_robust_std)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.0303 -0.5279 -0.2230  0.1617  6.7556 

Coefficients:
                                 Estimate Std. Error t value Pr(>|t|)
(Intercept)                    -3.187e-17  9.227e-02   0.000    1.000
autonomous_maintenance_count   -1.495e-01  1.175e-01  -1.273    0.206
focused_maintenance_count       1.400e-01  1.077e-01   1.299    0.196
planned_maintenance_count      -1.908e-02  1.057e-01  -0.180    0.857
quality_maintenance_count      -2.742e-02  1.187e-01  -0.231    0.818
education_and_training_count    1.009e-01  1.186e-01   0.851    0.397
office_tpm_count                4.242e-02  1.004e-01   0.423    0.673
development_management_count   -4.107e-02  1.114e-01  -0.369    0.713
safety_health_environment_count 1.468e-01  1.232e-01   1.191    0.236

Residual standard error: 1.007 on 110 degrees of freedom
Multiple R-squared:  0.05561,	Adjusted R-squared:  -0.01308 
F-statistic: 0.8096 on 8 and 110 DF,  p-value: 0.5955
```

Robustness test 2: logistic regression model (presence)

```
Call:
glm(formula = availability ~ autonomous_maintenance + focused_maintenance +
    planned_maintenance + quality_maintenance + education_and_training +
    office_tpm + development_management + safety_health_environment,
    family = "binomial", data = data_coded_robust_validated)

Coefficients:
                              Estimate Std. Error z value Pr(>|z|)
(Intercept)                    0.33567    1.89540   0.177  0.85943
autonomous_maintenanceTRUE    -1.51581    0.92386  -1.641  0.10085
focused_maintenanceTRUE        2.21411    0.82747   2.676  0.00746 **
planned_maintenanceTRUE       -1.80284    1.40712  -1.281  0.20012
quality_maintenanceTRUE        0.04112    1.03483   0.040  0.96830
education_and_trainingTRUE     2.95690    1.11677   2.648  0.00810 **
office_tpmTRUE                 0.18184    0.47186   0.385  0.69997
development_managementTRUE     0.39456    0.78141   0.505  0.61360
safety_health_environmentTRUE -1.38976    1.83725  -0.756  0.44939
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 136.51  on 118  degrees of freedom
Residual deviance: 119.86  on 110  degrees of freedom
AIC: 137.86

Number of Fisher Scoring iterations: 5
```

Robustness test 3: logistic regression model (count)

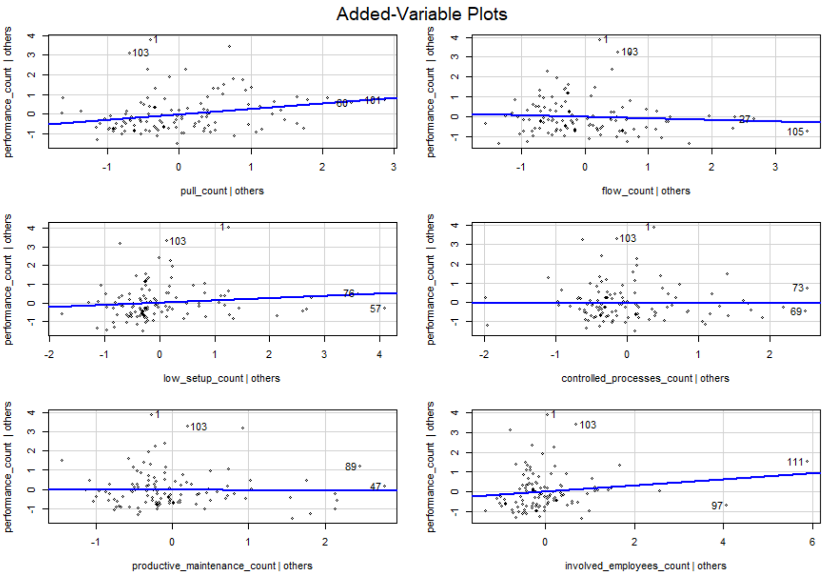
```
Call:
glm(formula = availability ~ ., family = "binomial", data = model1_logreg_robust2_std)

Coefficients:
                               Estimate Std. Error z value Pr(>|z|)
(Intercept)                     1.48333    0.30337   4.890 1.01e-06 ***
autonomous_maintenance_count   -0.15136    0.31969  -0.473    0.636
focused_maintenance_count      -0.22204    0.29940  -0.742    0.458
planned_maintenance_count       1.87683    0.72875   2.575    0.010 *
quality_maintenance_count       0.14920    0.36815   0.405    0.685
education_and_training_count    0.31773    0.39353   0.807    0.419
office_tpm_count               -0.04224    0.26780  -0.158    0.875
development_management_count    0.11662    0.30931   0.377    0.706
safety_health_environment_count 0.23208    0.38021   0.610    0.542
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 136.51  on 118  degrees of freedom
Residual deviance: 118.47  on 110  degrees of freedom
AIC: 136.47

Number of Fisher Scoring iterations: 6
```

H2: LM→ performance

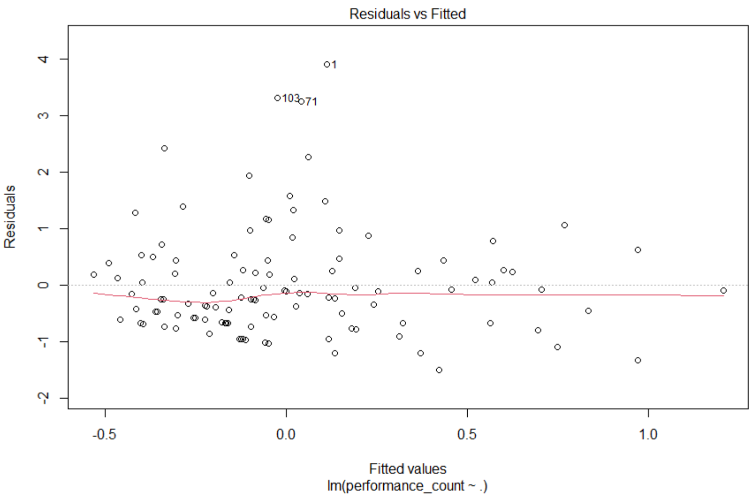
Baseline model

```
Call:
lm(formula = performance_count ~ ., data = model2_std)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.4917 -0.6541 -0.2169  0.2665  3.9124 

Coefficients:
                              Estimate Std. Error t value Pr(>|t|)   
(Intercept)                  5.396e-16  8.795e-02   0.000  1.00000   
pull_count                   2.798e-01  1.038e-01   2.695  0.00812 **
flow_count                  -8.567e-02  1.033e-01  -0.829  0.40881   
low_setup_count              1.226e-01  9.614e-02   1.275  0.20488   
controlled_processes_count  -8.003e-03  1.161e-01  -0.069  0.94518   
productive_maintenance_count -3.128e-02  1.168e-01  -0.268  0.78934   
involved_employees_count     1.561e-01  9.865e-02   1.582  0.11646   
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9594 on 112 degrees of freedom
Multiple R-squared:  0.1263,    Adjusted R-squared:  0.07953 
F-statistic: 2.699 on 6 and 112 DF,  p-value: 0.01742
```

Checking Assumptions: Linear relationship



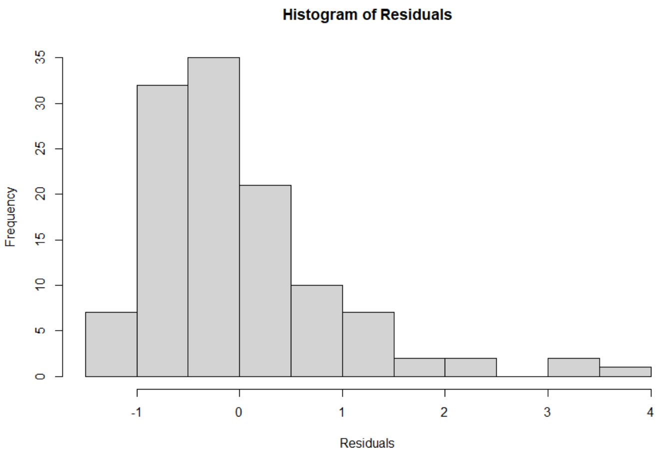
Checking Assumptions: Constant variance / uncorrelated error term

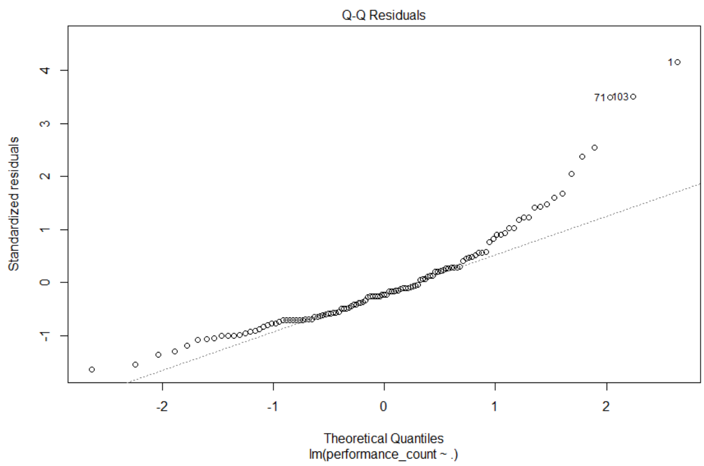


Checking Assumptions: No perfect multicollinearity (VIF)

```
                  pull_count                   flow_count              low_setup_count  controlled_processes_count
                    1.381768                     1.368630                     1.184787                    1.729069
productive_maintenance_count   involved_employees_count
                    1.748447                     1.247605
```

Checking Assumptions: Normality of the error term





Robustness test 1: linear regression model (robust version)

```
Call:
lm(formula = performance_count ~ ., data = model2_robust_std)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.5387 -0.6239 -0.2319  0.3623  4.0548 

Coefficients:
                              Estimate Std. Error t value Pr(>|t|)   
(Intercept)                  5.538e-16  8.856e-02   0.000  1.00000   
pull_count                   2.804e-01  1.054e-01   2.659  0.00899 **
flow_count                  -3.813e-02  9.931e-02  -0.384  0.70173   
low_setup_count             -2.338e-02  9.199e-02  -0.254  0.79988   
controlled_processes_count  -2.264e-02  1.165e-01  -0.194  0.84631   
productive_maintenance_count -3.131e-02  1.181e-01  -0.265  0.79146   
involved_employees_count     1.787e-01  9.872e-02   1.811  0.07289 . 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.9661 on 112 degrees of freedom
Multiple R-squared:  0.1142,    Adjusted R-squared:  0.0667 
F-statistic: 2.406 on 6 and 112 DF,  p-value: 0.03177
```

Robustness test 2: logistic regression model (presence)

```
Call:
glm(formula = performance ~ pull + flow + low_setup + controlled_processes +
    productive_maintenance + involved_employees, family = "binomial",
    data = data_coded_robust_validated)

Coefficients:
                           Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -0.3792     0.6592  -0.575   0.5651
pullTRUE                     1.4043     0.7103   1.977   0.0480 *
flowTRUE                     0.3268     0.5734   0.570   0.5687
low_setupTRUE               -0.2366     0.8581  -0.276   0.7827
controlled_processesTRUE    -0.1461     0.7284  -0.201   0.8411
productive_maintenanceTRUE   0.5155     0.6480   0.795   0.4264
involved_employeesTRUE       1.3217     0.5947   2.223   0.0262 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 101.124  on 118  degrees of freedom
Residual deviance:  86.642  on 112  degrees of freedom
AIC: 100.64

Number of Fisher Scoring iterations: 5
```

Robustness test 3: logistic regression model (count)

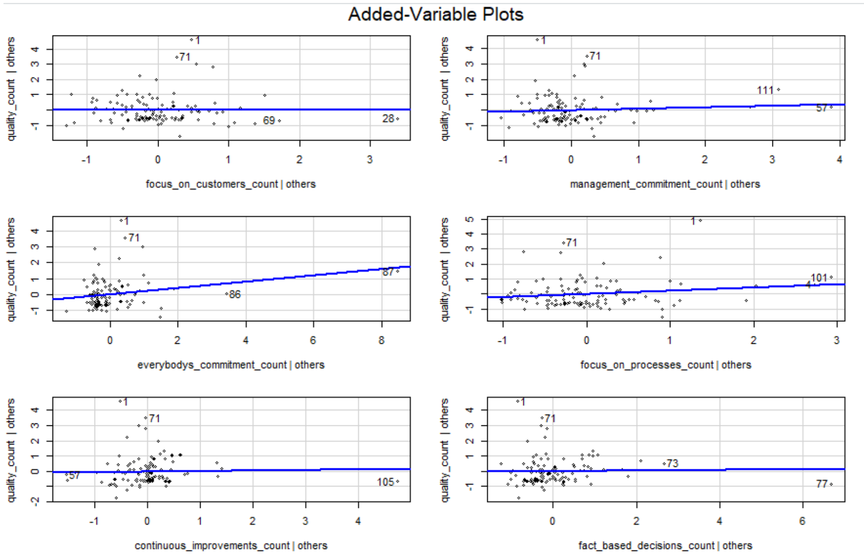
```
Call:
glm(formula = performance ~ ., family = "binomial", data = model2_logreg_robust2_std)

Coefficients:
                             Estimate Std. Error z value Pr(>|z|)
(Intercept)                  2.297262   0.432517   5.311 1.09e-07 ***
pull_count                   0.582958   0.396865   1.469   0.1419
flow_count                   0.074673   0.417240   0.179   0.8580
low_setup_count              0.008438   0.451527   0.019   0.9851
controlled_processes_count   0.076293   0.455148   0.168   0.8669
productive_maintenance_count 0.171555   0.456529   0.376   0.7071
involved_employees_count     1.307007   0.778223   1.679   0.0931 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 101.12  on 118  degrees of freedom
Residual deviance:  88.98  on 112  degrees of freedom
AIC: 102.98

Number of Fisher Scoring iterations: 6
```

H3: TQM→ quality

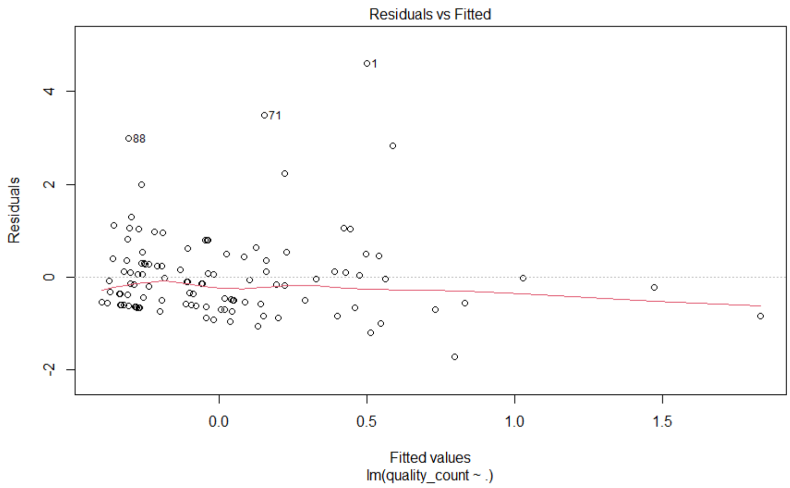
Baseline model

```
Call:
lm(formula = quality_count ~ ., data = model3_std)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.7265 -0.5954 -0.1594  0.2943  4.6011 

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)  
(Intercept)                6.213e-16  8.700e-02   0.000   1.0000  
focus_on_customers_count   2.791e-03  1.401e-01   0.020   0.9841  
management_commitment_count 9.236e-02 1.298e-01  0.712   0.4782  
everybodys_commitment_count 2.000e-01 8.833e-02  2.265   0.0255 *
focus_on_processes_count   2.097e-01  1.293e-01   1.622   0.1075  
continuous_improvements_count 3.506e-02 1.366e-01 0.257  0.7978  
fact_based_decisions_count 2.285e-02  9.776e-02   0.234   0.8156  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.949 on 112 degrees of freedom
Multiple R-squared:  0.1451,	Adjusted R-squared:  0.09934 
F-statistic: 3.169 on 6 and 112 DF,  p-value: 0.006564
```

Checking Assumptions: Linear relationship



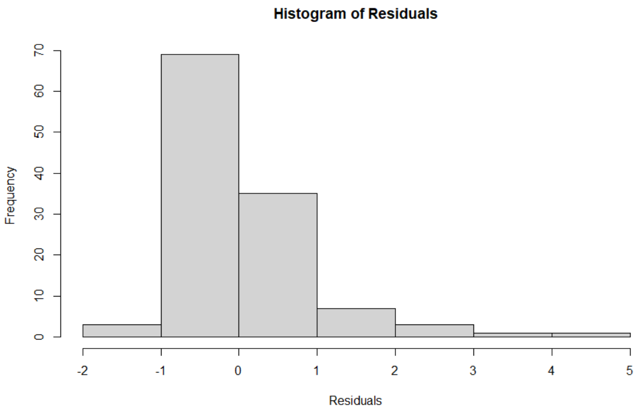
Checking Assumptions: Constant variance / uncorrelated error term

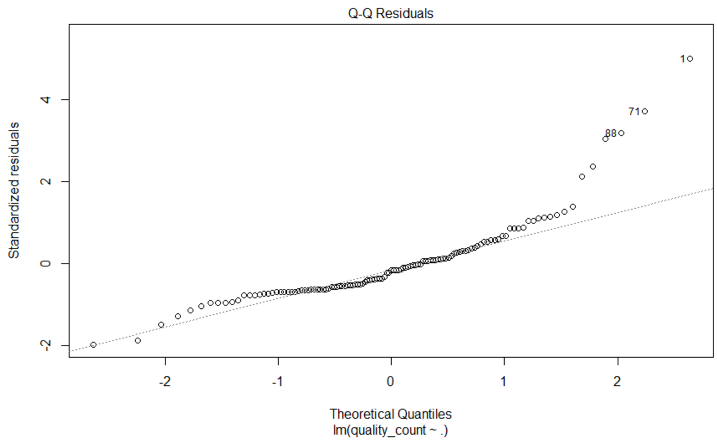


Checking Assumptions: No perfect multicollinearity (VIF)

```
focus_on_customers_count    management_commitment_count    everybodys_commitment_count
                2.570532                       2.207347                       1.022186
focus_on_processes_count continuous_improvements_count     fact_based_decisions_count
                2.189199                       2.442956                       1.252226
```

Checking Assumptions: Normality of the error term





Robustness test 1: linear regression model (robust version)

```
Call:
lm(formula = quality_count ~ ., data = model3_robust_std)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.7265 -0.5954 -0.1594  0.2943  4.6011 

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)  
(Intercept)                 6.213e-16  8.700e-02   0.000   1.0000  
focus_on_customers_count    2.791e-03  1.401e-01   0.020   0.9841  
management_commitment_count 9.236e-02  1.298e-01   0.712   0.4782  
everybodys_commitment_count 2.000e-01  8.833e-02   2.265   0.0255 *
focus_on_processes_count    2.097e-01  1.293e-01   1.622   0.1075  
continuous_improvements_count 3.506e-02  1.366e-01   0.257   0.7978  
fact_based_decisions_count  2.285e-02  9.776e-02   0.234   0.8156  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.949 on 112 degrees of freedom
Multiple R-squared:  0.1451,    Adjusted R-squared:  0.09934 
F-statistic: 3.169 on 6 and 112 DF,  p-value: 0.006564
```

Robustness test 2: logistic regression model (presence)

```
Call:
glm(formula = quality ~ focus_on_customers + management_commitment +
    everybodys_commitment + focus_on_processes + continuous_improvements +
    fact_based_decisions, family = "binomial", data = data_coded_robust_validated)

Coefficients:
                             Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -16.61862 1384.75286  -0.012   0.9904
focus_on_customersTRUE        0.15250    0.84653   0.180   0.8570
management_commitmentTRUE     0.05957    1.15943   0.051   0.9590
everybodys_commitmentTRUE     1.02699    0.58610   1.752   0.0797 .
focus_on_processesTRUE        0.60665    0.60205   1.008   0.3136
continuous_improvementsTRUE  15.86897 1384.75328   0.011   0.9909
fact_based_decisionsTRUE      1.66989    0.65383   2.554   0.0106 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 116.844  on 118  degrees of freedom
Residual deviance:  92.684  on 112  degrees of freedom
AIC: 106.68

Number of Fisher Scoring iterations: 15
```

Robustness test 3: logistic regression model (count)

```
Call:
glm(formula = quality ~ ., family = "binomial", data = model3_logreg_robust2_std)

Coefficients:
                              Estimate Std. Error z value Pr(>|z|)
(Intercept)                     2.5498     0.5142   4.959 7.09e-07 ***
focus_on_customers_count       -1.2321     0.6978  -1.766   0.0775 .
management_commitment_count     0.6778     0.7139   0.950   0.3424
everybodys_commitment_count     0.4957     0.6743   0.735   0.4622
focus_on_processes_count        0.4298     0.4736   0.908   0.3641
continuous_improvements_count   1.5939     1.1682   1.364   0.1725
fact_based_decisions_count      2.0410     0.8069   2.529   0.0114 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 116.844  on 118  degrees of freedom
Residual deviance:  89.649  on 112  degrees of freedom
AIC: 103.65

Number of Fisher Scoring iterations: 7
```